Forecasting Stock Market Returns: 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) as high as 1.6% with monthly data and 16.9% 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 0.33 higher relative to using the historical mean. Our results are robust in international data. We conclude that there is substantial predictability in stock returns and that it would have been possible to time the market in real time.

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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), Campbell and Yogo (2006), Ang and Bekaert (2007), Cochrane (2008), Binsbergen and Koijen (2009), and many others use the dividend yield; Campbell and Shiller (1988) and Lamont (1998) use the earnings-price ratio; 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 per-

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

formance 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 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 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* (SOP). 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 three alternatives to predict the growth rate in the price-earnings ratio. In the first alternative, we assume no growth in the price-earnings ratio (i.e., the return forecast equals the sum of the dividend yield and earnings growth forecasts). In the second alternative, we use predictive regressions for the growth rate in the price-earnings ratio. In the third 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.[2]

We apply the SOP method using the same data as Goyal and Welch (2008) for the 1927-2007 period.[3] 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

[2] We apply shrinkage to the regression coefficients in the SOP method (in both alternatives two and three) to improve the robustness of the predictions. Parenthetically, we show that shrinkage also improves significantly the out-of-sample performance of traditional predictive regressions.

[3] The sample period in Goyal and Welch (2008) is 1927-2004. We use the more recent data, but the results would actually slightly improve if we use only the 1927-2004 period.

the historical mean) that range from 0.68% to 1.55% with monthly data and from 4.65% to 16.94% with yearly data (and non-overlapping observations). Moreover, we obtain significant out-of-sample R-squares of 1.32% with monthly data and 13.43% with yearly data just by using the SOP method with no multiple growth. 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 with the predictive regression approach used by Goyal and Welch (2008). Our results are robust in subsamples and in international data. The SOP method performs remarkably well with data from the U.K. and Japan, where there is even stronger predictability in stock returns than in the U.S..

The economic gains from a trading strategy that uses the SOP method are substantial. The certainty equivalent gains of applying the SOP 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 0.30% 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 stock returns and that it would have been possible to time the market in real time.

We conduct a Monte Carlo simulation experiment to better understand the performance of the SOP method. We use the Campbell and Shiller (1988) present-value method with i.i.d. dividend growth and expected returns following an AR(1) process calibrated to the data. We find that the median root mean square error (relative to the true return expected return, which is known in the simulation) of the SOP estimator is 2.17% versus 4.75% and 4.54% for the historical mean and predictive regressions, respectively. The simulation results clearly show the superiority of the SOP method to forecast stock market returns.

The remainder of the paper is organized as follows. Section 1 describes the methodology. Section 2 describes the data and presents the results. Section 3 presents results of a simulation analysis. Section 4 concludes.

1. 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.

1.1 Forecasting Returns with Predictive Regressions

The traditional *predictive regression* methodology regresses stock returns on lagged predictors:[4]

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

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 denote the conditional expected return by $\mu_s = \mathrm{E}_s(r_{s+1})$ where $\mathrm{E}_s(\cdot)$ is the expectation operator conditional on the information available at time s. We then use the estimated coefficients of the predictive regression (denoted with hats) and the value of the predictive variable at time s to predict the return at time $s+1$:[5]

$$\hat{\mu}_s = \hat{\alpha} + \hat{\beta} x_s. \tag{2}$$

We follow this process for $s = s_0, ..., T-1$, thereby generating a sequence of out-of-sample return forecasts $\hat{\mu}_s$. 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

[4] Alternatives to predictive regressions based on Bayesian methods, latent variables, analyst forecasts, and surveys have been suggested by several authors (Welch (2000), Claus and Thomas (2001), Brandt and Kang (2004), Pastor and Stambaugh (2008), Binsbergen and Koijen (2009)).

[5] 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 s for simplicity.

similar to the one proposed by Goyal and Welch (2008).[6] This measure compares the predictive ability of the regression with the historical sample mean (which implicitly assumes that expected returns are constant):

$$R^2 = 1 - \frac{MSE_A}{MSE_M}, \tag{3}$$

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

$$MSE_A = \frac{1}{T - s_0} \sum_{s=s_0}^{T-1} \left(r_{s+1} - \hat{\mu}_s\right)^2, \tag{4}$$

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.[7] 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.

We evaluate the statistical significance of the results using the $MSE{-}F$ statistic proposed by McCracken (2007) that tests for equal MSE of the unconditional (historical mean) and conditional forecasts:

$$MSE - F = (T - s_0)\left(\frac{MSE_M - MSE_A}{MSE_A}\right). \tag{6}$$

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

[7] Goyal and Welch (2008) include a degree-of-freedom adjustment in their R-square 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.

In the tables we do not report the $MSE-F$ statistics but use their critical values to provide statistical significance using stars.

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).[8] We transform the estimated coefficients of equation (2) by:

$$\beta^* = \frac{s}{s+i}\hat{\beta}, \tag{7}$$

$$\alpha^* = \overline{r}_s - \beta^* \overline{x}_s, \tag{8}$$

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

[8]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.

R-square:

$$\rho = E\left(\frac{R^2}{1-R^2}\right) \approx E(R^2). \tag{9}$$

This is the expected explanatory power of the model. We use $i = 100$ with yearly 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 yearly data and less than 0.1% with monthly data which seems reasonable in light of the findings in the 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.[9]

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

$$\hat{\mu}_s = \alpha^* + \beta^* x_s. \tag{10}$$

1.2 Return Components

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

$$1 + R_{t+1} = 1 + CG_{t+1} + DY_{t+1} = \frac{P_{t+1}}{P_t} + \frac{D_{t+1}}{P_t}, \tag{11}$$

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 per share paid during the return period.[10]

[9] As an alternative we could have used the approach of Jansson and Moreira (2006) applied to forecasting by Eliasz (2005).

[10] Bogle (1991b), Bogle (1991a), Fama and French (1998), Arnott and Bernstein (2002), and Ibbotson and Chen (2003) offer similar decompositions of returns.

The capital gain component can be written as follows:

$$
\begin{aligned}
1 + CG_{t+1} &= \frac{P_{t+1}}{P_t} \\
&= \frac{P_{t+1}/E_{t+1}}{P_t/E_t}\frac{E_{t+1}}{E_t} \\
&= \frac{M_{t+1}}{M_t}\frac{E_{t+1}}{E_t} \\
&= (1 + GM_{t+1})(1 + GE_{t+1}),
\end{aligned}
\tag{12}
$$

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 rate. 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, the price-to-book ratio, or the price-to-sales ratio.[11] In these alternatives, we should replace the growth in earnings by the growth rate of the denominator in the multiple (i.e., dividends, book value of equity, or sales).

The dividend yield can in turn be decomposed as follows:

$$
\begin{aligned}
DY_{t+1} &= \frac{D_{t+1}}{P_t} \\
&= \frac{D_{t+1}}{P_{t+1}}\frac{P_{t+1}}{P_t} \\
&= DP_{t+1}(1 + GM_{t+1})(1 + GE_{t+1}),
\end{aligned}
\tag{13}
$$

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 (11), we can write the total return as the product of the dividend-price ratio and the growth rates of the price-earnings

[11] In our empirical application we obtain similar findings using return decompositions based on the price-dividend, price-to-book, or price-to-sales ratios.

ratio and growth rate of earnings:

$$\begin{aligned} 1 + R_{t+1} &= (1 + GM_{t+1})(1 + GE_{t+1}) + DP_{t+1}(1 + GM_{t+1})(1 + GE_{t+1}) \\ &= (1 + GM_{t+1})(1 + GE_{t+1})(1 + DP_{t+1}). \end{aligned} \tag{14}$$

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

$$\begin{aligned} r_{t+1} &= \log(1 + R_{t+1}) \\ &= gm_{t+1} + ge_{t+1} + dp_{t+1}, \end{aligned} \tag{15}$$

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

1.3 The Sum-of-the-Parts Method (SOP)

As an alternative to the predictive regressions, we propose forecasting separately the components of the stock market return from expression (15):

$$\hat{\mu}_s = \hat{\mu}_s^{gm} + \hat{\mu}_s^{ge} + \hat{\mu}_s^{dp}. \tag{16}$$

We estimate the expected earnings growth $\hat{\mu}_s^{ge}$ using a 20-year moving average of the growth in earnings per share up to time s. 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 $\hat{\mu}_s^{dp}$ 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 three alternative methods to forecast the growth in the price-earnings multiple.

In the first approach, we simply assume *no multiple growth*, i.e., $\hat{\mu}_s^{gm} = 0$. Assuming that the price-earnings multiple does not change fits closely with the random walk hypothesis for the dividend-price ratio.

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

$$gm_{t+1} = \alpha + \beta x_t + \epsilon_{t+1}, \tag{17}$$

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. Similarly to the predictive regression approach (see equations (7)-(9)), we apply shrinkage to the estimated coefficients:

$$\beta^* = \frac{s}{s+i}\hat{\beta}, \tag{18}$$

$$\alpha^* = -\beta^* \overline{x}_s, \tag{19}$$

thereby shrinking the intercept to make the unconditional mean of the multiple growth equal to zero.

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

$$m_t = a + b x_t + u_t. \tag{20}$$

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:

$$\widehat{m}_s = \hat{a} + \hat{b} x_s. \tag{21}$$

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:

$$\begin{aligned} -\hat{u}_s &= \widehat{m}_s - m_s \\ &= \hat{\mu}_s^{gm}. \end{aligned} \tag{22}$$

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 (20):

$$gm_{t+1} = c + d\left(-\hat{u}_t\right) + v_t. \tag{23}$$

We apply again shrinkage to the estimated coefficients as follows:

$$d^* = \frac{s}{s+i}\hat{d}, \tag{24}$$

$$c^* = -d^*\left(-\overline{\hat{u}}_s\right) \tag{25}$$

$$= d^*\overline{\hat{u}}_s \tag{26}$$

where $\overline{\hat{u}}_s$ is the sample mean of the regression residuals up to time s (not necessarily equal to zero). 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:

$$\hat{\mu}_s^{gm} = c^* + d^* \left(-\hat{u}_s\right). \tag{27}$$

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

2. Empirical Analysis

2.1 Data

We use the data set constructed by Goyal and Welch (2008).[12] We use monthly data to predict the monthly stock market return and yearly data (non-overlapping) to predict the yearly stock market return.[13] 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. It is clear that average returns are driven mostly by earnings growth and the dividend yield while most of the return volatility comes from earnings growth and the multiple growth. Crucially for predictive purposes, the time series properties of the return components are very different. The dividend-price ratio is very persistent, with an AR(1) coefficient of 0.79 at the annual frequency. In contrast the

[12] 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.

[13] 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.

AR(1) coefficients of earnings growth and multiple growth are close to zero.[14]

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.

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).

[14] Earnings growth shows substantial persistence at the monthly frequency but that is due to the fact that we measure earnings over the previous 12 months and there is therefore substantial overlap in the series from one month to the next.

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 SOP method with multiple growth regression and with multiple reversion. In the latter approach we do not use the predictors that directly depend on the stock index price (EP, SEP, DP, DY, and BM).

2.2 Main Results

In this section we perform an out-of-sample forecasting exercise along the lines of Goyal and Welch (2008). Table 2 reports 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 starts next to the In-sample R-square denote significance of the in-sample regression as measured by the F-statistic. The stars next to the Out-of-sample R-squares denote whether the performance of the conditional forecast is statistically different from the unconditional forecasts (i.e., historical mean) using the McCracken (2007) MSE-F statistic.

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%. Overall, there are only four variables significant at the 5% level.

The remaining columns evaluate the out-of-sample performance of the alternative forecasts using the out-of-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 column present out-of-sample R-squares of forecasting separately the components of the stock market return (SOP method) assuming no multiple growth. The seventh column uses the SOP method with multiple growth regression, while the eighth column uses the SOP method with multiple reversion.

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% (which is significant at the 1% level).

Second, shrinkage improves the out-of-sample performance of most predictors. There are now 8 variables with positive R-squares out of 16 variables, although only two are significant at the 5% level. 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 price and earnings growth components alone. The the out-of-sample R-square of using only the dividend price and earnings growth components to forecast stock market returns (SOP with no multiple growth). We obtain an out-of-sample R-square of 1.32% (significant at the 1% level), which is much better than the performance of the traditional predictive regressions. The R-squares from the SOP method with multiple growth regression are all positive and 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. All the SOP method forecasts are significant at the 1% level under the McCracken (2007) MSE-F statistic.

Finally, there is similar good performance when we forecast the price-earnings growth using the SOP method with multiple reversion approach. We present R-squares for only those variables that do not depend on the stock index price.[15] The last column shows that 4 (out 11 variables) have higher R-squares than in the multiple growth regression approach. The R-square coefficients of the multiple reversion approach range from 0.69% to 1.39%. 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, that is assuming that the price earnings ratio reverts to its historical mean. We obtain a remarkable R-square of 1.35%.

Figure 2 shows the realized price-earnings ratio and the fitted value from regression equation (20) of the price earnings on three different explanatory variables: SVAR, TMS, and TBL. This is one of the steps to obtain return forecasts in the SOP method with multiple reversion. It is interesting 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 in equation (23) captures this speed of adjustment. The expected return coming from the SOP method with 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 from the

[15] We do not use EP, SEP, DP, DY, and BM in the multiple reversion approach since running a contemporaneous regression of the price-earnings ratio on other multiples does not make sense.

SOP method with multiple reversion 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 substantial time variation.

Figure 4 compares the expected return from the SOP method (with multiple reversion) with traditional predictive regressions and 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 SOP method estimates.

Figure 5 shows the three versions of the SOP forecasts with three alternative predictive variables (SVAR, TMS, and TBL). Of course, the forecasts under the SOP method with no multiple growth are the same in the three panels. The three versions of the SOP method are highly correlated, but the SOP with multiple reversion forecast displays more variability. In the first panel (SVAR) we can see a spike in the SOP method with multiple reversion because there is an outlier in volatility in October 1987. This sensitivity to outliers is a weakness of this version of the SOP.

Figure 6 shows cumulative out-of-sample R-squares for both the SOP method (with multiple reversion) 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 at the annual frequency: 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 yearly frequency. Using annual return forecasts, the SOP method with multiple reversion presents the best performance (in particular relative to the SOP method with 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 yearly frequency (13 out of 16 variables) consistent with Goyal and Welch (2008). The R-squares range from -17.57% to 7.54%, but only one variable is significant at the 5% level. Using shrinkage with the traditional predictive regression gives eleven variables with positive R-squares, but only two significant at the 5% level. Forecasting separately the components of stock market returns dramatically improves the performance. We obtain an R-square of 13.43% (significant at the 1% level) when we use only the dividends and earnings growth components to forecast stock market returns (SOP method with no multiple growth). When we add the forecast of the price-earnings growth from a predictive regression (SOP method with multiple growth 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). Furthermore, under the SOP method all variables are statistically significant at the 1% level.

It is instructive to compare our results with 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 a decomposition of expected stock returns based on the Gordon growth model (and earnings growth is entirely financed by retained earnings).Their method is a special case of equation (16) with $\mu_s^{gm} = 0$ and $\mu_s^{ge} = [1 - E_t(\mathrm{DE}_{t+1})] E_t(\mathrm{ROE}_{t+1})$, (i.e., expected plowback times return on equity). 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 plowback (or one minus 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% (significant at the 5% level) with monthly frequency and 3.24% (significant only at the 10% level) with yearly frequency.[16] 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, both significant at the 1% level. When we include the multiple growth component, the R-squares are even higher as shown in Table 2. The SOP method forecasting performance is substantially better for two reasons: our forecast of earnings growth works better and our forecast of the price-earnings growth has incremental explanatory power.

2.3 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 January 1927 to December 1976 and from January 1957 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 3 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).

Consistent with Goyal and Welch (2008), the out-of-sample performance 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). We find that the SOP method dominates the traditional predictive regressions in both subsamples and generated significant gains in performance relative to the historical mean.

[16] 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.

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 and it is the only significant variable at the 5% level.

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 (both significant at the 5% level). The maximum R-squares using the SOP method with multiple growth regression are 2.29% in the first subperiod and 1.44% in the second subperiod (both significant at the 1% level). This is much better than the performance of the traditional predictive regressions. There is similar good performance when we use the SOP method with multiple reversion. The maximum R-squares are roughly 2% (9 out of 11 variables in the first subperiod) and 1% (in the second subperiod) and they are all significant at the 5% level with only a single exception.

At the annual frequency, we find that most variables have worse performance in the most recent subperiod, but the SOP 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 and significant 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 (both significant at the 1% level). This is much better than the performance of the traditional predictive regressions.

2.4 Trading Strategies

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

$$w_s = \frac{E_s(r_{s+1}) - rf_{s+1}}{\gamma\sigma_s^2} \tag{28}$$

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;[17] and σ_s^2 is the variance of the stock market returns that we estimate using all the available data up to time s. The only thing that varies across portfolio policies are the estimates of the expected returns either from the predictive regressions or the SOP method. Note that these portfolio policies could have been implemented in real time with data available at the time of the decision.[18]

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

$$rp_{s+1} = w_s r_{s+1} + (1 - w_s) rf_{s+1}. \tag{29}$$

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:

$$ce = \overline{rp} - \frac{\gamma}{2}\sigma^2(rp). \tag{30}$$

where $\overline{rp}$ is the sample mean portfolio return and $\sigma^2(rp)$ is the sample variance portfolio

[17] 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.

[18] In unreported results, we obtain 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% leverage ($w_s \leq 150\%$).

return. This is the risk-free return that a mean-variance investor with a risk-aversion coefficient γ 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 gain in Sharpe ratio (annualized) for each strategy.

Table 4 reports the certainty equivalent gains (in percentage) relative to investing based on the historical mean. Using the historical mean, the certainty equivalents are 7.4% and 6.4% per year at the monthly and yearly 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 SOP method always leads to economic gains. 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 SOP method with multiple growth regression and multiple reversion are 2.33% and 1.72% per year. We obtain similar results using annual (and non-overlapping) returns.

Table 5 reports the gains in Sharpe ratio 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 traditional predictive regressions leads to losses relative to the historical mean in most cases. Applying shrinkage to the traditional predictive regression improves the performance of the trading strategies. Most important, the SOP method always leads to Sharpe ratio gains. In fact, using only the dividend yield and earnings growth components (SOP method with no multiple growth), we obtain a Sharpe ratio gain of 0.31. The maximum gains in the multiple growth regression and multiple reversion approaches are 0.33 and 0.24. 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 0.1 gain in Sharpe ratio.

2.5 International Evidence

In this section, we repeat our analysis in Table 2 using international data. We obtain data on stock price indices and dividends from Global Financial Data (GFD) for the U.K. and Japan, which are the two largest stock markets in the world after the U.S.. The sample period is from 1950 to 2007, which is shorter than in Table 2 because of data availability. We report results using stock market returns in local currency at the annual frequency, but we obtain consistent results using returns at the monthly frequency or returns is U.S. dollars. We consider three macro variables (LTY, TMS and TBL obtained also from GFD) and the dividend yield (DY) as predictors because these are the variable that are available for a longer sample period. We apply here the SOP method using the price dividend as multiple rather than the price earnings since earnings for the U.K. and Japan are only available for a shorter period

Panels A and B present the results for the U.K. and Japan and Panel C presents the results for the U.S. in the comparable sample period (1950-2007) and also using the price dividend as multiple. The traditional predictive regression R-squares are in general negative, consistent with our previous findings. The R-squares range from -47.54% to 3.12%, and none is significant at the 5% level. Using shrinkage with the traditional prediction regression improves performance and the dividend yield is now significant at the 5% level in the U.K. and Japan (only at the 10% level in the U.S.). Forecasting separately the components of stock market returns dramatically improves the performance. We obtain R-squares of 10.73% and 12.14% (both significant at the 1% level) in the U.K. and Japan when we use only the dividends and earnings growth components to forecast stock market returns (SOP method with no multiple growth). When we add the forecast of the price-earnings growth from a predictive regression (SOP method with multiple growth regression), we obtain an even higher R-square for some variables: 13.28% (in Japan using the dividend yield). When we alternatively add the forecast of the price-earnings growth from the multiple reversion approach, the R-squares reach values of more than 11% in the U.K. and Japan. Furthermore, under the SOP method with multiple reversion all variables are statistically significant at the 5% level. Interestingly, the performance of the SOP method is better in the U.K. and Japan than in the U.S. when we redo the analysis for the U.S. for the comparable sample period and using price dividend as a multiple (Panel C). In any case, the SOP method clearly dominates predictive regressions using U.S. data.

Figure 7 shows expected returns for the U.K., Japan, and the U.S. according to the three SOP variants. There are substantial differences, with the U.K. generally offering the highest expected returns (around 11.7% on average) while expected returns in Japan are the lowest through most of the sample (4.7% on average). At times, the difference in expected returns across countries is as high as 12%. There is more variability in expected returns in the U.K. and Japan than in the U.S.. Interestingly, the correlation between expected returns in the U.K. and the U.S. is high (of the order of 0.7) but Japanese expected returns have negative correlations with both the U.K. and U.S. markets (of the order of -0.3).

2.6 Analyst Forecasts

An alternative forecast of earnings can be obtained from analyst estimates drawn from I/B/E/S and aggregated across all S&P 500 stocks. We use these forecasts to calculate both the price earnings ratio and the earnings growth. Panel A of Table 7 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 1.60% and 3.10%. However, using our previous approach works even better than analyst forecasts in this sample period, with out-of-sample R-squares between 2.81% and 4.66%. This is consistent with the well-known bias in analyst forecasts.

3. Simulation Analysis

In this section we conduct a Monte Carlo simulation experiment to better understand the performance of the SOP method with no multiple growth. We consider an economy where expected returns follow a highly persistent AR(1) process and dividend-growth is assumed to be i.i.d., consistent with the analysis of Cochrane (2008). Applying the Campbell and Shiller (1988) present-value identity to this model allows us to pin down the exact relation between realized returns, expected returns, and the log dividend-price ratio.

The processes for conditional expected returns and dividend growth are assumed to be:

$$\mu_{t+1} = a + b\mu_t + \varepsilon^{\mu}_{t+1}, \tag{31}$$

$$\Delta d_{t+1} = \bar{g} + \varepsilon^{d}_{t+1}, \tag{32}$$

where d is the log of dividends per share and the innovations follow a Normal distribution:

$$\begin{bmatrix} \varepsilon^{\mu}_{t+1} \\ \varepsilon^{d}_{t+1} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{\mu} & \sigma_{\mu d} \\ \sigma_{\mu d} & \sigma^2_{d} \end{bmatrix} \right), \tag{33}$$

and a, b, $\bar{g}$, σ_{μ}, σ_d, and $\sigma_{\mu d}$ are constant.

Campbell and Shiller (1988) show that the log dividend-price ratio is given by:

$$d_t - p_t = \sum_{k=0}^{+\infty} \rho^k \mathrm{E}_t \left[\mu_{t+k}\right] - \sum_{k=0}^{+\infty} \rho^k \mathrm{E}_t \left[\Delta d_{t+k+1}\right] - \kappa,$$

where κ and ρ are constants from the log-linearization. Given the processes (31) and (32), we can obtain simple expressions for the infinite sums above:

$$d_t - p_t = \alpha_{\mu} + \beta_{\mu}\mu_t, \tag{34}$$

where:

$$\alpha_\mu = \left[\frac{a}{\left(1+\frac{D}{P}-b\right)} - \bar{g}\right]\frac{1+\frac{D}{P}}{\frac{D}{P}} - \kappa, \tag{35}$$

$$\beta_\mu = \left[\frac{1+\frac{D}{P}}{1+\frac{D}{P}-b}\right], \tag{36}$$

and $\frac{D}{P}$ is the dividend-price ratio.

We can also obtain an expression for returns:

$$r_{t+1} = \alpha_r + \beta_r\left(d_t - p_t\right) + \varepsilon^r_{t+1}, \tag{37}$$

where:

$$\alpha_r = \left(1+\frac{D}{P}-b\right)\left[\frac{\ln\left(1+\frac{D}{P}\right)}{\frac{D}{P}} - \frac{\ln\left(\frac{D}{P}\right)}{1+\frac{D}{P}} + \frac{\bar{g}}{\frac{D}{P}}\right] - a\frac{1}{\frac{D}{P}}, \tag{38}$$

$$\beta_r = \left(\frac{1+\frac{D}{P}-b}{1+\frac{D}{P}}\right). \tag{39}$$

The innovation to returns is, of course, related to the innovations in expected returns and dividend growth:

$$\varepsilon^r_{t+1} = \varepsilon^d_{t+1} - \frac{1}{1+\frac{D}{P}-b}\varepsilon^\mu_{t+1}. \tag{40}$$

Note that in this model there is a linear predictive relation between the dividend-price ratio and returns.

We simulate 10,000 samples of 80 years of returns (which is approximately the size of our empirical sample), dividend growth, and the dividend-price ratio for this economy using the following parameter values calibrated to our data:

$$a = 0.005\ ,\ b = 0.95\ ,\ \bar{g} = 0.05\ ,\ \sigma_d = 0.14\ ,\ \sigma_\mu = 0.016\ ,\ \sigma_{\mu d} = 0\ ,\ \frac{D}{P} = 0.04.$$

We use these simulated data to study the different return forecasting methods. The advantage of using Monte Carlo simulation is that we know the true expected return at each point in time. Thus, we can compare our forecasts with expected returns and not just with realized returns as we do in the empirical analysis.

We want to answer the question: Is the SOP method a better forecaster of realized returns than predictive regressions or the sample mean? In each simulation of the economy, we replicate our out-of-sample empirical analysis, i.e., we compute for each year the forecast of returns from the three approaches (historical mean, predictive regression, SOP method with no multiple growth) using only past data. The regressions use the log dividend-price ratio as predictive variable. We then compute the sum of the squares of the difference between the forecasted returns and the true expected returns from the simulation. Table 8 displays the percentiles (across simulations) of the root mean squared errors (RMSE) of each forecast method.

The results clearly show that the SOP method yields a better estimate of expected returns than predictive regressions or the sample mean of returns. The median RMSE of SOP method is 2.17% which is good in absolute terms and is less than half the corresponding statistics for the historical mean and predictive regressions. This difference persists across all the percentiles of the distribution of RMSE. The poor performance of predictive regressions is notable since in our simulated economy there is an exact linear forecasting relation between the dividend-price ratio and returns (see equation (37)). It can only be due to estimation error.

We can also investigate the distribution of out-of-sample R-squares in the Monte Carlo simulation. The 10th, 50th, and 90th percentiles of these out-of-sample R-squares for the SOP method are 1.34%, 4.94%, and 8.80%, respectively. The same percentiles of out-of-sample R-squares for predictive regressions are -8.20%, 0.16%, and 8.09%, respectively. Again the sum-of-the-parts approach is clearly superior.

4. Conclusion

We abandon predictive regressions of total stock returns in favor of separately forecasting the dividend yield, the earnings growth, and the price earnings growth components of stock market returns — the sum-of-the-parts (SOP) method. We apply the SOP method to forecast stock markets returns out-of-sample in the 1927-2007 period. The SOP method leads to statistically and economically significant gains for investors. These findings contrast with Goyal and Welch (2008) and revive the 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 parameters are unstable over time and because of estimation error. Most of the gains in performance in the SOP method come 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.

The 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 what we are capturing is excessive predictability rather than risk premia, the very success of our analysis will eventually destroy its usefulness. If that is the case, once a sufficiently large number of investors follow our approach to predict returns, they will impact market prices and again make returns unpredictable.

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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.

Panel A: Univariate Statistics								
	Mean	Median	Std Dev	Min	Max	Skew	Kurt	AR(1)
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
r	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
r	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*	*r*
gm	1			
ge	-0.35	1		
dp	-0.07	-0.20	1	
r	0.93	0.02	-0.13	1
Panel B.2: Annual frequency (1927 - 2007)				
	gm	*ge*	*dp*	*r*
gm	1			
ge	-0.66	1		
dp	-0.21	-0.16	1	
r	0.60	0.19	-0.38	1

Table 2
Forecasts of Stock Market Returns

This table presents in-sample and out-of-sample R-squares (in percentage) for stock market return forecasts at the monthly and annual (non-overlapping) frequencies. The in-sample R-squares are estimated over the full sample period. The out-of-sample R-squares compare the forecast error of the model with 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. A star next to in-sample R-squares denotes significance of the in-sample regression as measured by the F-statistic. A star next to out-of-sample R-squares denotes significance of the MSE-F statistic of McCracken (2007). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Description	In-sample R-square	Out-of-Sample R-square				
			Predictive regression	Predictive regression (shrinkage)	SOP no multiple growth	SOP multiple growth reg.	SOP multiple reversion
Panel A: Monthly returns			**Sample: December 1927 - December 2007**				
	–	–	–	–	1.32***	–	–
SVAR	Stock variance	0.05	−0.10	−0.02	–	0.91***	1.31***
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***	0.69***
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***	1.39***
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***	1.34***
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 earnings 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***
Panel B: Annual returns			**Sample: 1927 - 2007**				
	–	–	–	–	13.43***	–	–
SVAR	Stock variance	0.34	−0.15	0.00	–	12.74***	13.65***
DFR	Default return spread	1.95	1.64*	0.99	–	14.40***	12.98***
LTY	Long term bond yield	0.71	−8.31	−0.85	–	10.92***	7.61***
LTR	Long term bond return	2.29	−2.94	2.65**	–	12.62***	16.94***
INFL	Inflation	1.39	−1.04	0.53	–	12.91***	14.05***
TMS	Term spread	0.80	−7.23	−1.20	–	11.28***	15.57***
TBL	T-bill rate	0.13	−11.69	−2.09	–	11.51***	11.67***
DFY	Default yield spread	0.03	−1.13	−0.31	–	12.57***	14.46***
NTIS	Net equity expansion	12.29***	1.06*	2.30*	–	13.31***	14.21***
ROE	Return on equity	0.02	−10.79	−2.40	–	13.66***	9.02***
DE	Dividend payout	1.58	−0.17	0.47	–	12.60***	9.72***
EP	Earnings price	5.69**	7.54***	4.56**	–	14.31***	–
SEP	Smooth earnings 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***

Table 3
Forecasts of Stock Market Returns: Subsamples

This table presents in-sample and out-of-sample R-squares (in percentage) for stock market return forecasts at the monthly and annual (non-overlapping) frequencies. The in-sample R-squares are estimated over the full sample period. The out-of-sample R-squares compare the forecast error of the model with the forecast error of the historical mean. The sample period is from December 1927 to December 2007. The subsamples divide the data in half. Forecasts begin 20 years after the sample start. A star next to in-sample R-squares denotes significance of the in-sample regression as measured by the F-statistic. A star next to out-of-sample R-squares denotes significance of the MSE-F statistic of McCracken (2007). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Description	In-sample R-square	Out-of-Sample R-square: Predictive regression	Predictive regression (shrinkage)	SOP no multiple growth	SOP multiple growth reg.	SOP multiple reversion
Panel A.1: Monthly returns			**Sample: December 1927 - December 1976**				
	–	–	–	–	1.80***	–	–
SVAR	Stock variance	0.00	−0.18	−0.04	–	1.64***	2.13***
DFR	Default return spread	0.01	−1.04	−0.22	–	1.57***	2.10***
LTY	Long term bond yield	0.11	−1.72	0.04	–	1.61***	0.93***
LTR	Long term bond return	0.12	−2.20	−0.34	–	1.42***	2.21***
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 earnings 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***
Panel B.1: Annual returns			**Sample: 1927 - 1976**				
	–	–	–	–	14.66***	–	–
SVAR	Stock variance	0.19	−0.76	−0.21	–	13.93***	21.54***
DFR	Default return spread	2.34	4.52*	1.66	–	14.82***	20.17***
LTY	Long term bond yield	0.70	−10.95	−0.82	–	9.62**	13.40***
LTR	Long term bond return	6.82*	9.64*	5.10**	–	13.44***	25.18***
INFL	Inflation	1.49	−0.99	0.72	–	13.77***	22.18***
TMS	Term spread	1.91	−6.66	−0.68	–	12.80***	21.85***
TBL	T-bill rate	1.59	−12.14	−1.43	–	11.66**	18.31***
DFY	Default yield spread	0.05	−1.64	−0.43	–	14.56***	21.98***
NTIS	Net equity expansion	14.91***	0.65	0.31	–	14.59***	21.75***
ROE	Return on equity	0.91	−12.62	−1.93	–	14.73***	22.82***
DE	Dividend payout	1.30	−0.23	−0.12	–	13.09***	21.52***
EP	Earnings price	6.74*	14.14***	4.71*	–	21.77***	–
SEP	Smooth earnings price	22.44***	−10.42	5.91**	–	23.21***	–
DP	Dividend price	2.93	4.48*	1.82	–	21.02***	–
DY	Dividend yield	5.28	−17.74	4.34*	–	18.16***	–
BM	Book-to-market	14.73***	8.30***	4.41*	–	19.87***	–
	Constant	–	–	–	–	–	21.76***

Table 3: continued

Variable	Description	In-sample R-square	Out-of-Sample R-square				
			Predictive regression	Predictive regression (shrinkage)	SOP no multiple growth	SOP multiple growth reg.	SOP multiple reversion
Panel A.2: Monthly returns			**Sample: December 1956 - December 2007**				
	–	–	–	–	0.98**	–	–
SVAR	Stock variance	0.36	−0.99	−0.22	–	0.00	0.81**
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***	0.85**
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**	0.60**
NTIS	Net equity expansion	0.85**	0.53**	0.58**	–	1.44***	0.79**
ROE	Return on equity	0.12	−0.88	−0.09	–	0.62**	0.80**
DE	Dividend payout	0.00	−1.07	−0.17	–	0.74**	−0.19
EP	Earnings price	0.61*	0.30*	0.19*	–	0.87**	–
SEP	Smooth earnings 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**
Panel B.2: Annual returns			**Sample: 1956 - 2007**				
	–	–	–	–	12.10***	–	–
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 earnings 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**

Table 4
Trading Strategies: Certainty Equivalent Gains

This table presents out-of-sample portfolio choice results at the monthly and annual (non-overlapping) frequencies. The numbers are the certainty equivalent gains (in percentage) of a trading strategy timing the market with different return forecasts relative to timing the market with the historical mean return. 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 equivalent 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)	SOP no multiple growth	SOP multiple growth reg.	SOP multiple reversion
Panel A: Monthly returns		**Sample: December 1927 - December 2007**				
	–	–	–	1.79	–	–
SVAR	Stock variance	−0.04	0.00	–	0.97	1.61
DFR	Default return spread	−0.26	−0.04	–	1.75	1.72
LTY	Long term bond yield	−1.56	−0.29	–	1.76	1.26
LTR	Long term bond return	−0.25	0.10	–	1.92	1.68
INFL	Inflation	−0.07	−0.02	–	1.86	1.65
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	1.65
NTIS	Net equity expansion	2.14	0.94	–	2.33	1.59
ROE	Return on equity	0.28	0.17	–	1.69	1.18
DE	Dividend payout	1.40	0.57	–	1.56	0.94
EP	Earnings price	0.20	0.35	–	1.69	–
SEP	Smooth earnings 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
Panel B: Annual returns		**Sample: 1927 - 2007**				
	–	–	–	1.82	–	–
SVAR	Stock variance	0.12	0.04	–	1.66	1.54
DFR	Default return spread	0.48	0.20	–	2.07	1.51
LTY	Long term bond yield	−1.05	−0.19	–	1.75	0.92
LTR	Long term bond return	1.48	0.66	–	1.88	1.95
INFL	Inflation	−0.08	0.08	–	1.73	1.47
TMS	Term spread	−0.58	−0.08	–	1.52	1.84
TBL	T-bill rate	−1.48	−0.31	–	1.69	1.25
DFY	Default yield spread	−0.01	−0.01	–	1.58	1.65
NTIS	Net equity expansion	1.25	0.54	–	1.89	1.64
ROE	Return on equity	−1.09	−0.28	–	2.04	0.78
DE	Dividend payout	0.60	0.24	–	1.91	0.74
EP	Earnings price	0.58	0.34	–	1.66	–
SEP	Smooth earnings 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

Table 5
Trading Strategies: Sharpe Ratio Gains

This table presents out-of-sample portfolio choice results at the monthly and annual (non-overlapping) frequencies. The numbers are the the change in Sharpe ratio of a trading strategy timing the market with different return forecasts relative to timing the market with the historical mean return. The utility function is $E(R_p) - (\gamma/2)Var(R_p)$ with a risk-aversion coefficient of $\gamma = 2$. 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)	SOP no multiple growth	SOP multiple growth reg.	SOP multiple reversion
Panel A: Monthly returns		**Sample: December 1927 - December 2007**				
	–	–	–	0.31	–	–
SVAR	Stock variance	0.00	0.00	–	0.12	0.22
DFR	Default return spread	−0.06	−0.01	–	0.30	0.24
LTY	Long term bond yield	−0.25	−0.06	–	0.29	0.09
LTR	Long term bond return	−0.12	−0.02	–	0.23	0.24
INFL	Inflation	−0.04	−0.01	–	0.31	0.19
TMS	Term spread	−0.05	−0.02	–	0.28	0.23
TBL	T-bill rate	−0.18	−0.04	–	0.32	0.16
DFY	Default yield spread	−0.02	0.00	–	0.33	0.24
NTIS	Net equity expansion	0.04	0.06	–	0.28	0.24
ROE	Return on equity	−0.06	−0.02	–	0.27	0.12
DE	Dividend payout	−0.02	0.00	–	0.32	0.14
EP	Earnings price	−0.09	0.30	–	0.23	–
SEP	Smooth earnings price	−0.21	0.12	–	0.12	–
DP	Dividend price	0.11	0.08	–	0.14	–
DY	Dividend yield	−0.13	0.15	–	0.07	–
BM	Book-to-market	−0.34	0.04	–	0.01	–
	Constant	–	–	–	–	0.24
Panel B: Annual returns		**Sample: 1927 - 2007**				
	–	–	–	0.22	–	–
SVAR	Stock variance	0.01	0.00	–	0.23	0.11
DFR	Default return spread	0.03	0.02	–	0.23	0.12
LTY	Long term bond yield	−0.14	−0.03	–	0.19	0.02
LTR	Long term bond return	0.08	0.06	–	0.23	0.15
INFL	Inflation	0.01	0.02	–	0.21	0.09
TMS	Term spread	−0.10	−0.02	–	0.18	0.15
TBL	T-bill rate	−0.19	−0.04	–	0.19	0.08
DFY	Default yield spread	−0.01	−0.01	–	0.24	0.13
NTIS	Net equity expansion	0.05	0.04	–	0.22	0.12
ROE	Return on equity	−0.15	−0.04	–	0.16	0.03
DE	Dividend payout	0.00	0.00	–	0.21	0.04
EP	Earnings price	0.05	0.15	–	0.12	–
SEP	Smooth earnings price	−0.15	0.07	–	0.06	–
DP	Dividend price	−0.02	0.02	–	0.04	–
DY	Dividend yield	−0.21	0.07	–	0.20	–
BM	Book-to-market	−0.19	0.03	–	0.09	–
	Constant	–	–	–	–	0.13

Table 6
Forecasts of Stock Market Returns: International Evidence

This table presents in-sample and out-of-sample R-squares (in percentage) for stock market return forecasts at the annual (non-overlapping) frequencies in the U.K. (Panel A), Japan (Panel B), and the U.S. (Panel C). The in-sample R-squares are estimated over the full sample period. The out-of-sample R-squares compare the forecast error of the model with the forecast error of the historical mean. The sample period is from 1950 or 1960 (as indicated in sample start) to 2007. Forecasts begin 20 years after the sample start. A star next to in-sample R-squares denotes significance of the in-sample regression as measured by the F-statistic. A star next to out-of-sample R-squares denotes significance of the MSE-F statistic of McCracken (2007). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Description	Sample start	In-sample R-square	Out-of-Sample R-square: Predictive regression	Predictive regression (shrinkage)	SOP no multiple growth	SOP multiple growth reg.	SOP multiple reversion
Panel A: U.K. annual returns								
	–	1950	–	–	–	10.73***	–	–
LTY	Long term bond yield	1950	5.29*	−47.54	−5.61	–	4.16**	11.27***
TMS	Term spread	1950	3.10	−14.71	−1.13	–	9.26**	11.60***
TBL	T-bill rate	1950	1.47	−20.87	−3.07	–	6.39**	11.51***
DY	Dividend yield	1950	11.97***	−9.19	5.07**	–	13.28***	10.78***
	Constant	1950	–	–	–	–	–	11.75***
Panel B: Japan annual returns								
	–	1950	–	–	–	12.14***	–	–
LTY	Long term bond yield	1950	1.69	−11.01	−1.86	–	12.11***	11.87***
TMS	Term spread	1960	0.36	−5.46	−0.89	–	5.75**	5.82**
TBL	T-bill rate	1960	1.76	−7.57	−0.62	–	5.14*	5.62**
DY	Dividend yield	1950	15.24***	3.12*	6.63**	–	10.25***	11.99***
	Constant	1950	–	–	–	–	–	11.91***
Panel C: U.S. annual returns								
	–	1950	–	–	–	7.75**	–	–
LTY	Long term bond yield	1950	0.17	−20.73	−1.51	–	4.47**	3.12*
TMS	Term spread	1950	1.11	−12.05	−0.99	–	8.24**	5.50**
TBL	T-bill rate	1950	0.03	−21.18	−2.00	–	5.06_{**}	3.40*
DY	Dividend yield	1950	7.95**	0.96	2.68*	–	6.64_{**}	5.73**
	Constant	1950	–	–	–	–	–	5.92**

Table 7
Forecasts of Stock Market Returns: Analyst Earnings Forecasts

This table presents in-sample and out-of-sample R-squares (in percentage) for stock market return forecasts at the monthly and annual (non-overlapping) frequencies. The in-sample R-squares are estimated over the full sample period. The out-of-sample R-squares compare the forecast error of the model with the forecast error of the historical mean. Panel A uses analyst earnings forecasts to calculate *gm* and *ge*. Panel B uses historical earnings to forecast *ge* and *gm*. The sample period is from December 1927 to December 2007. Forecasts begin 20 years after the sample start. A star next to in-sample R-squares denotes significance of the in-sample regression as measured by the F-statistic. A star next to out-of-sample R-squares denotes significance of the MSE-F statistic of McCracken (2007). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Description	In-sample R-square	Out-of-Sample R-square: Predictive regression	Predictive regression (shrinkage)	SOP no multiple growth	SOP multiple growth reg.	SOP multiple reversion
Panel A: Analysts forecasts			**Sample: January 1982 - December 2007**				
	–	–	–	–	2.32***	–	–
SVAR	Stock variance	0.88	−2.97	−0.17	–	2.26***	2.15***
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***	3.10***
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***	2.13***
TMS	Term spread	0.01	−2.00	−0.15	–	2.15***	2.07***
TBL	T-bill rate	0.29	−1.18	−0.03	–	2.19***	2.60***
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***	2.37***
ROE	Return on equity	0.02	−1.84	−0.10	–	1.97***	2.23***
DE	Dividend payout	0.02	−1.79	−0.12	–	2.26***	1.70***
EP	Earnings price	2.68***	1.78***	0.56*	–	2.39***	–
SEP	Smooth earnings 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***
Panel B: Historical data			**Sample: January 1982 - December 2007**				
	–	–	–	–	3.62***	–	–
SVAR	Stock variance	0.88	−2.97	−0.17	–	2.81***	3.59***
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***	3.62***
TMS	Term spread	0.01	−2.00	−0.15	–	3.22***	3.59***
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***	3.50***
NTIS	Net equity expansion	0.66	−1.23	0.06	–	2.97***	3.62***
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***	3.13***
EP	Earnings price	2.68***	1.78***	0.56*	–	3.61***	–
SEP	Smooth earnings 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***

Table 8
Monte Carlo Simulation: Percentiles of Root Mean Square Errors

This table presents the results of a Monte Carlo simulation considering an economy where expected returns follow an AR(1) process and dividend-growth is assumed to be i.i.d.. The simulation generates 10,000 samples of 80 years of returns, dividend growth, and the dividend-price ratio for this economy. In each simulation of the economy, annual forecast of returns are estimated, alternatively, under the historical mean, predictive regression with the log dividend-price ratio as conditioning variable, and SOP with no multiple growth methods using only past data. The forecast errors are given by the difference between the return forecasts and the true expected returns from the simulation. The table reports the percentiles (across simulations) of the root mean squared errors (RMSE) of each method.

Percentile	Historical mean	Predictive regression	SOP no multiple growth
10th	3.17	2.62	1.19
25th	3.85	3.42	1.57
50th	4.75	4.54	2.17
75th	5.92	5.96	3.04
90th	7.21	7.45	4.09

Figure 1. Cumulative Realized Stock Market Components

This figure shows monthly cumulative realized price-earnings ratio growth (gm), earnings growth (ge), dividend price (dp), and stock market return (r).

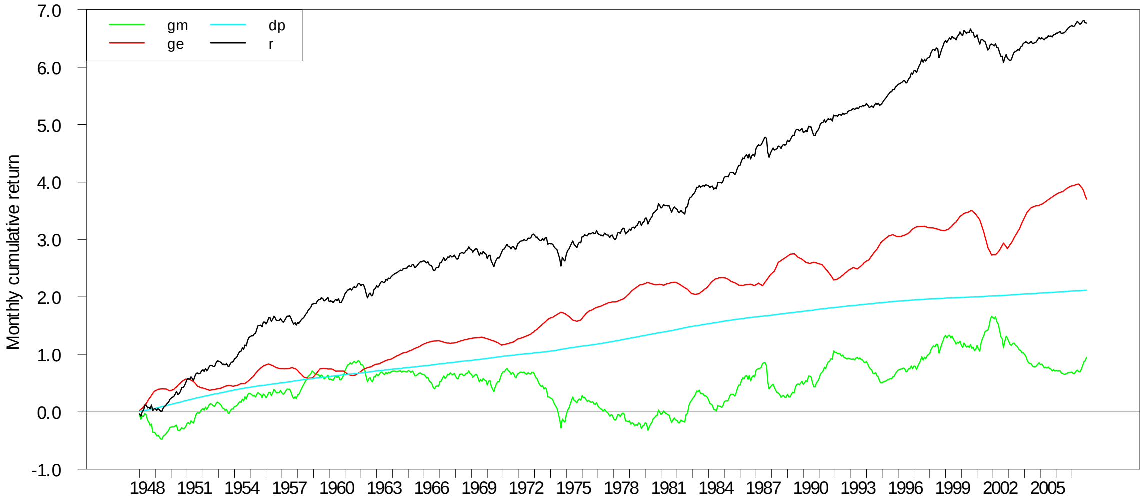


Figure 2. Realized and Forecasted Price Earnings Ratio

These figures show monthly realized and forecasted price-earnings ratio from the sum-of-the-parts method (SOP) with multiple reversion using alternative predictors.

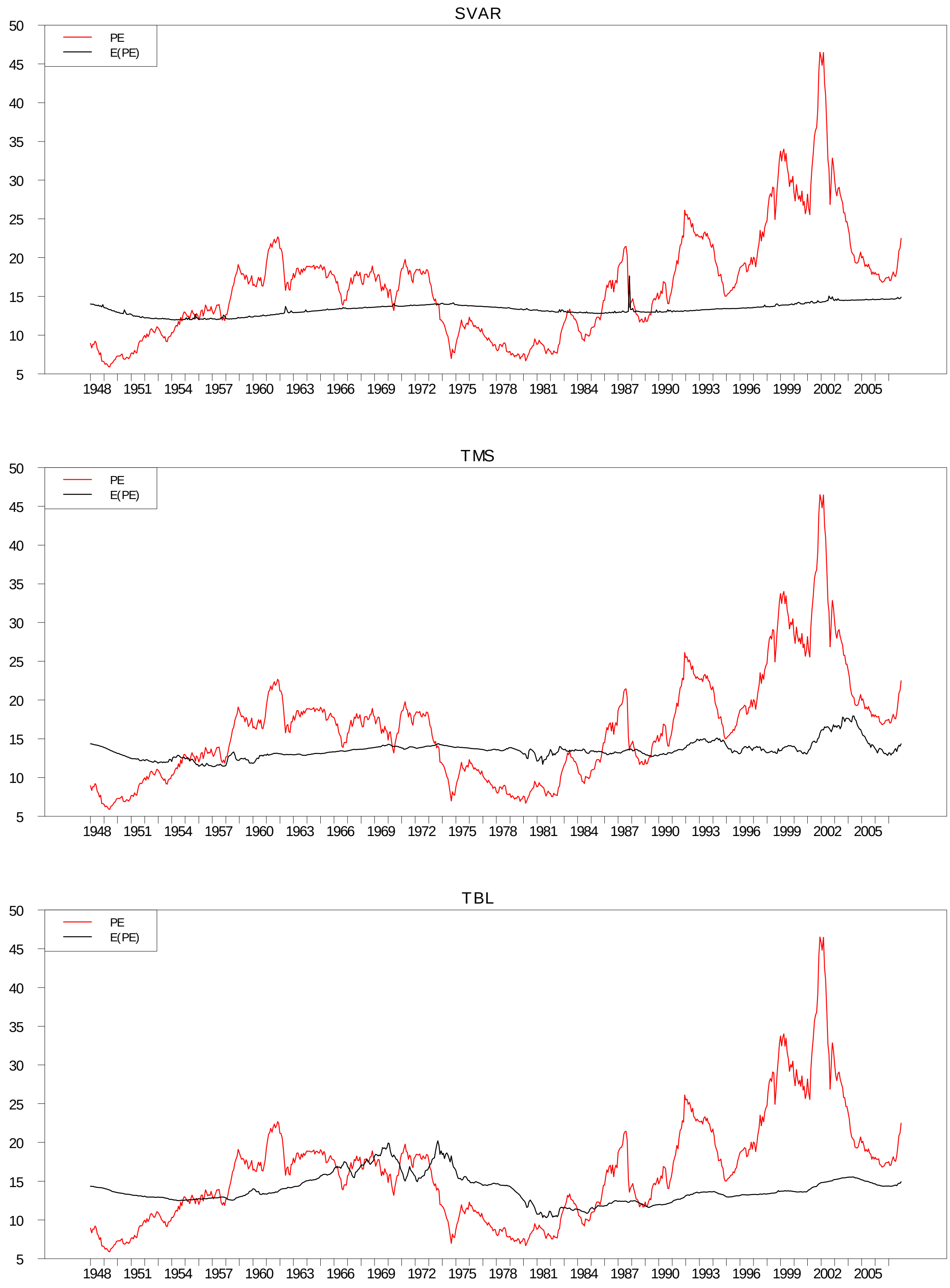


Figure 3. Forecasts of Stock Market Return Components

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 (SOP) method with multiple reversion using alternative predictors.

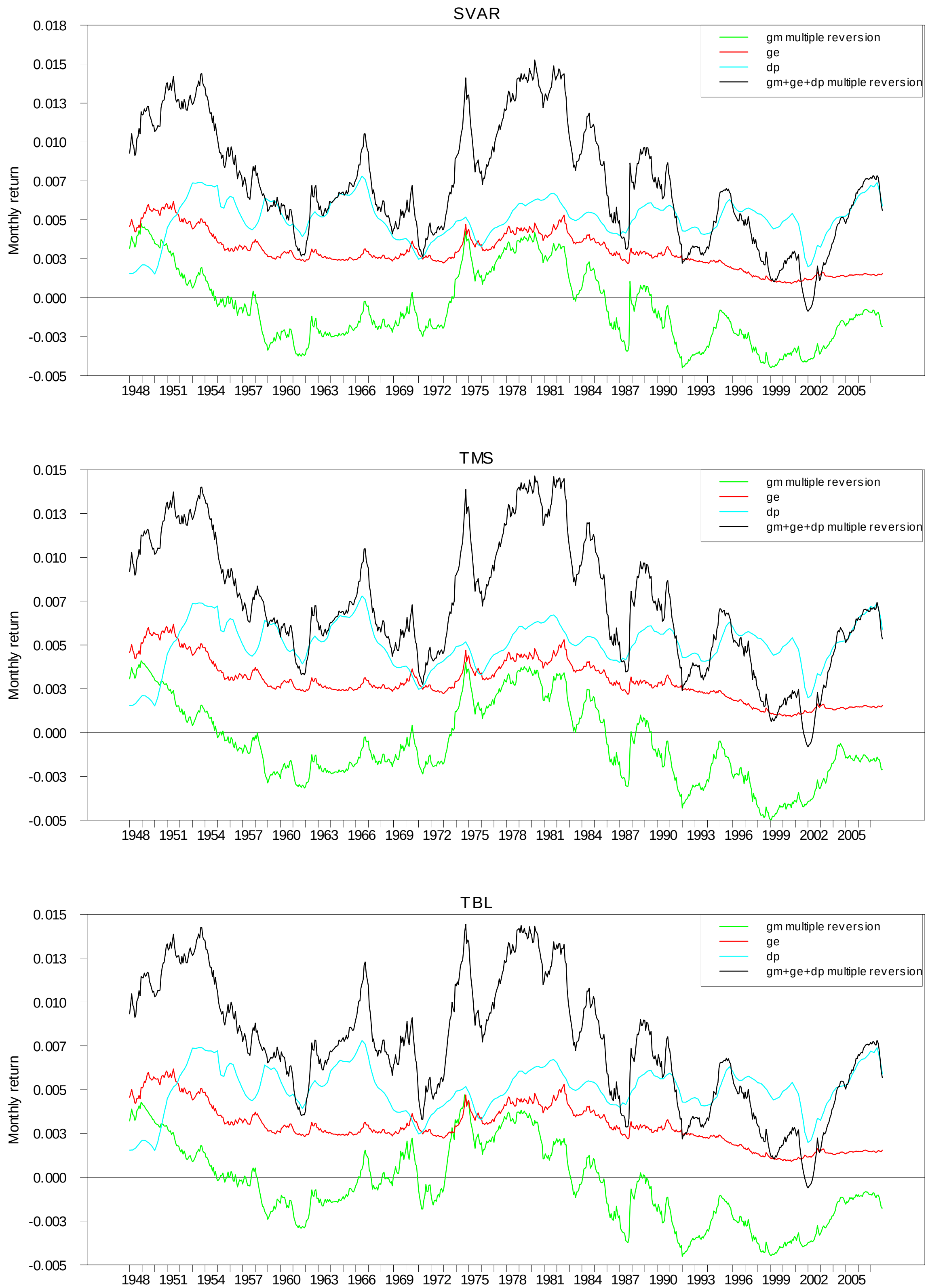
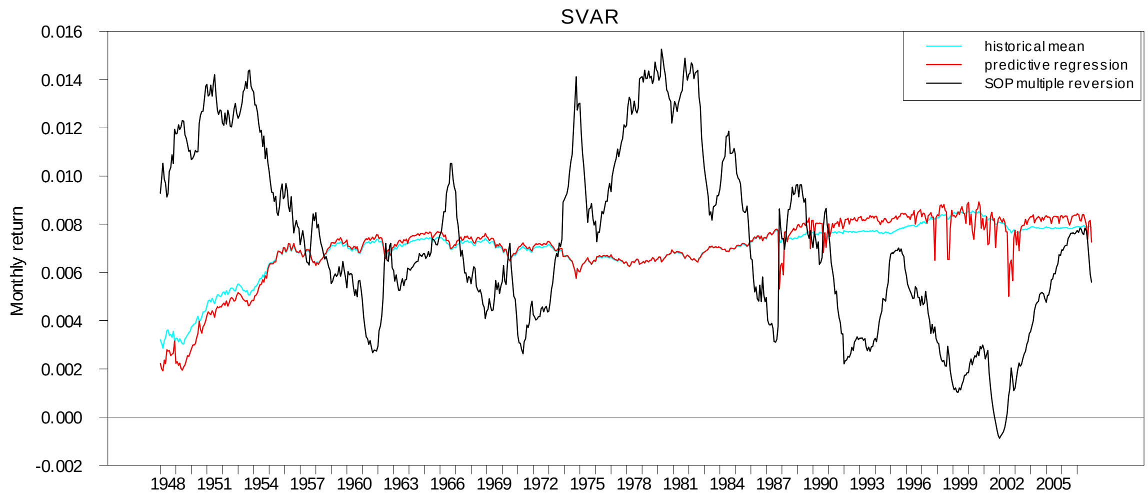
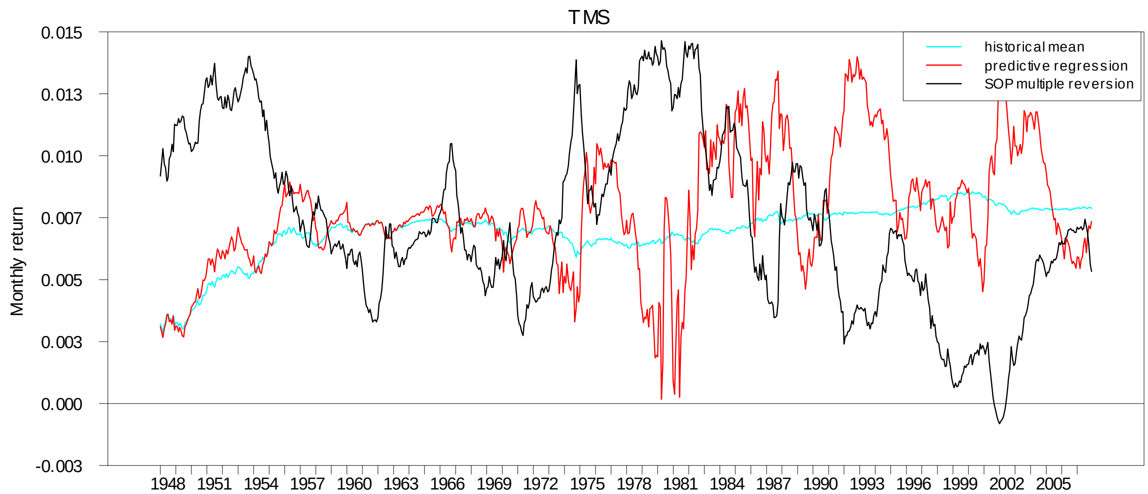


Figure 4. Forecasts of Stock Market Returns of Alternative Methods
These figures show monthly forecasts of market return from historical mean, predictive regressions, and sum-of-the-parts method (SOP) with multiple reversion using alternative predictors.





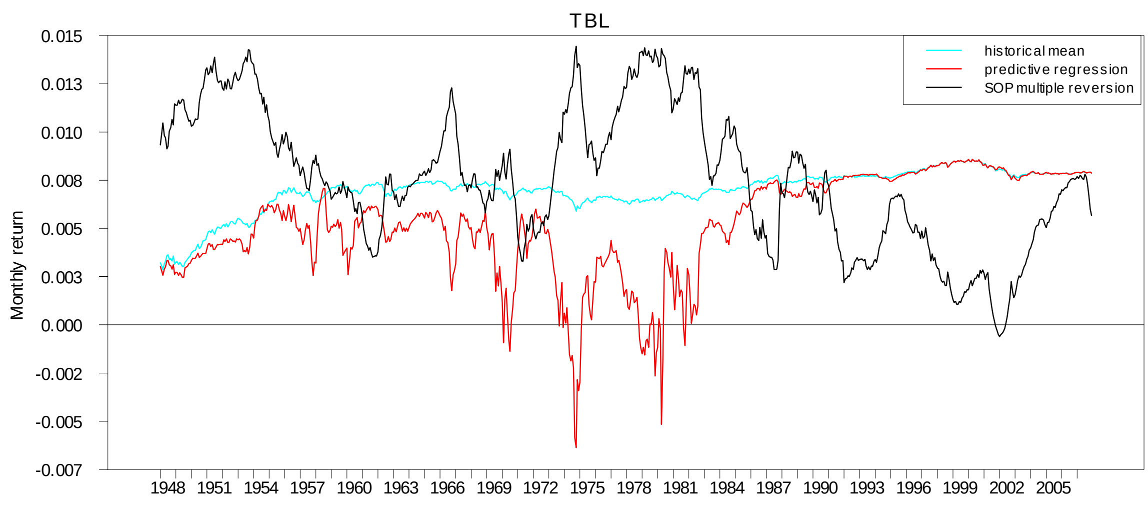
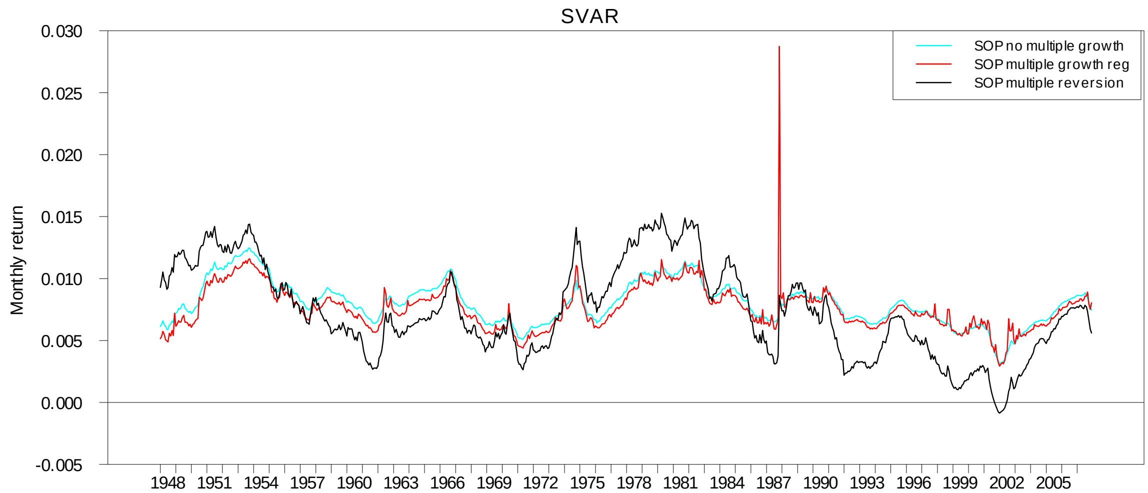
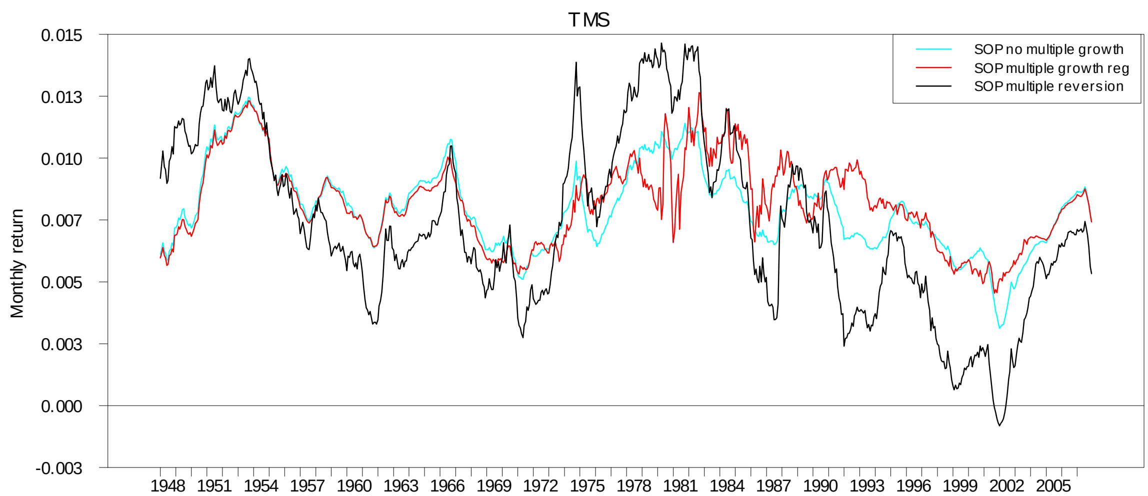


Figure 5. Forecasts of Stock Market Returns Using Alternative Sum-of-the-Parts Methods

These figures show monthly forecasts of market return from the sum-of-the-parts method (SOP) with no multiple growth, with multiple growth regression, and with multiple reversion.





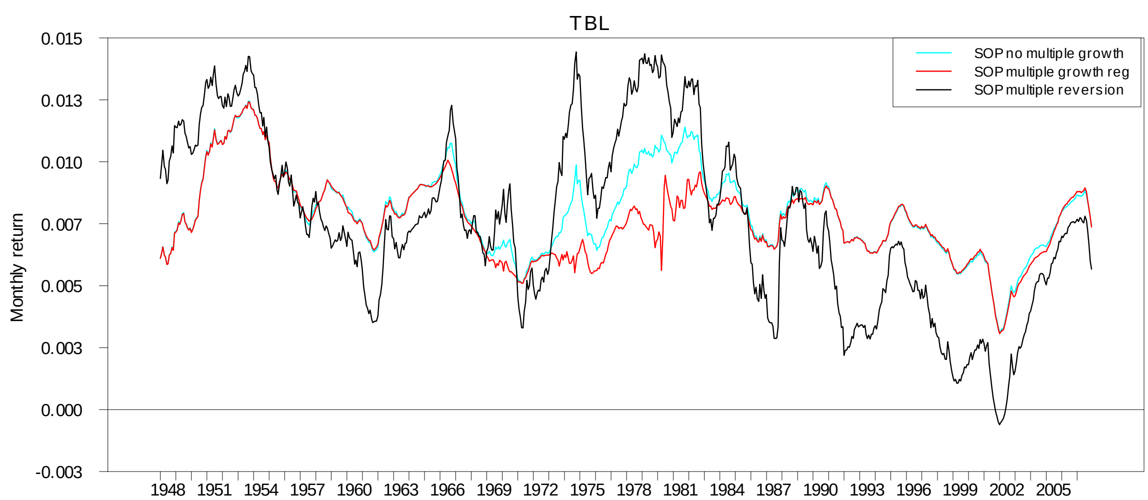


Figure 6. Cumulative R-square versus Historical Mean

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

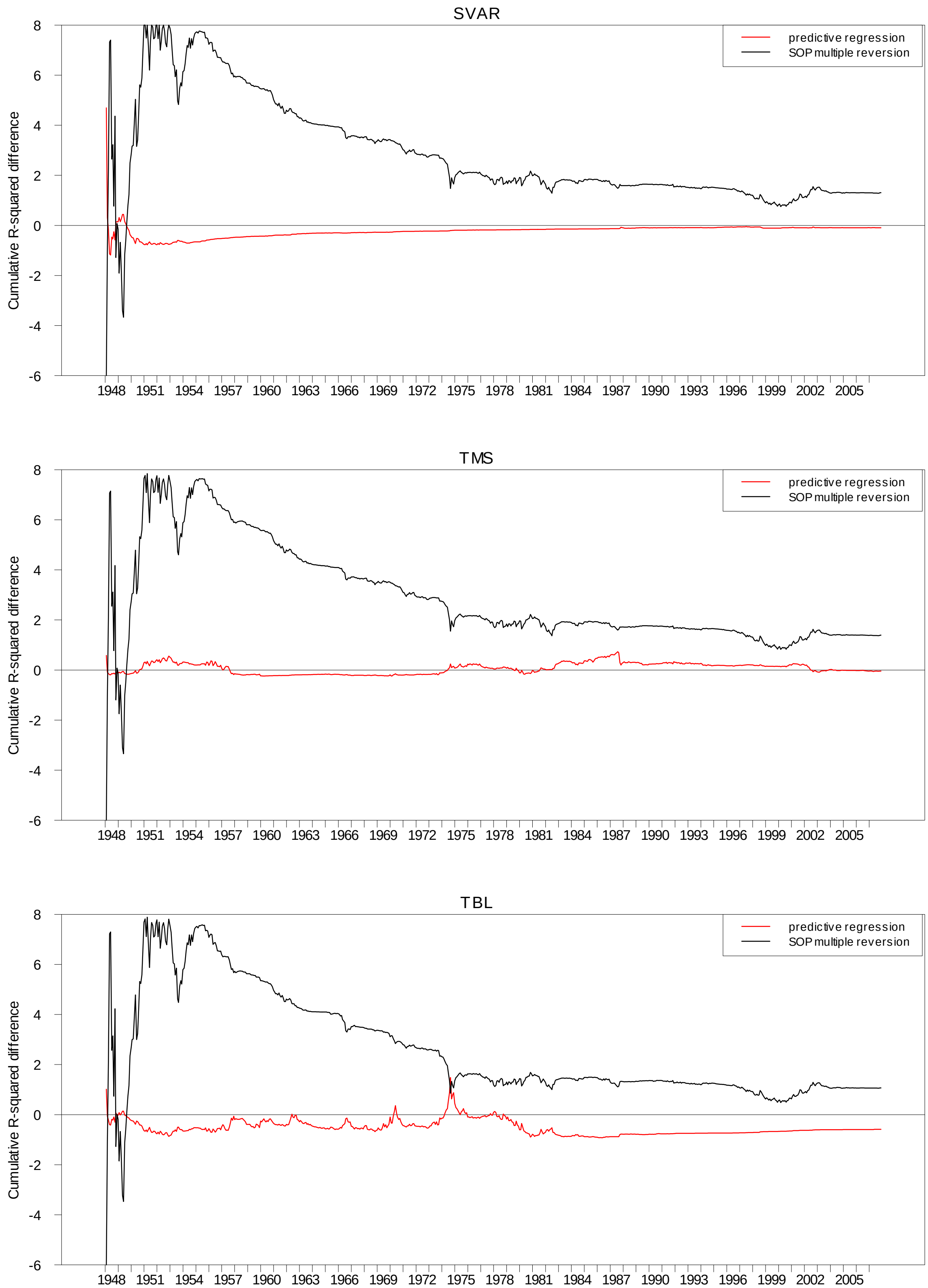


Figure 7. Forecasts of Stock Market Returns Using the Sum-of-the-Parts Method: International Evidence

These figures show annual forecasts of market return from the sum-of-the-parts method (SOP) with no multiple growth, with multiple growth regression, and with multiple reversion in the U.K., Japan, and the U.S.. The predictor is the long term bond yield.