Can Economic Uncertainty, Financial Stress and Consumer Sentiments Predict U.S. Equity Premium?

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Abstract

This article attempts to examine whether the equity premium in the United States can be predicted from a comprehensive set of 18 economic and financial predictors over a monthly out-of-sample period of 2000:2 to 2011:12, using an in-sample period of 1990:2-2000:1. To do so, we consider, in addition to the set of variables used in Rapach and Zhou (2013), the forecasting ability of four other important variables: the US economic policy uncertainty, the equity market uncertainty, the University of Michigan's index of consumer sentiment, and the Kansas City Fed's financial stress index. Using a more recent dataset compared to that of Rapach and Zhou (2013), our results from predictive regressions show that the newly added variables do not play any significant statistical role in explaining the equity premium relative to the historical average benchmark over the out-of-sample horizon, even though they are believed to possess valuable informative content about the state of the economy and financial markets. Interestingly, however, barring the economic policy uncertainty index, the three other indexes considered in this study yields economically significant out-of-sample gains, especially during recessions, when compared to the historical benchmark.

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1. Introduction

A considerable number of studies have dealt with predictability of stock market returns, using different predictors and methods (e.g., Avramov, 2002, 2004; Ang and Bekaert, 2007; Boudoukh et al., 2008). This long literature forecasts market returns using price multiples, corporate actions, measures of risk, and macroeconomic variables (see, e.g., Rapach et al., 2005; Gupta and Modise, 2012a,b for a brief review of this literature). Most of these studies find evidence in favour of return predictability in the in-sample forecasts (e.g., Campbell, 1999, 2000). Others find that certain components of the stock market returns have different time series persistence which facilitates return predictability (Rapach et al., 2011), but other components are difficult to forecast (Ferreira and Santa-Clara, 2011).

The in-sample forecastability behavior can be explained by specific factors related to market microstructure including transactions costs, information asymmetry, and agent heterogeneity (e.g., long-term investors, speculators, and hedge funds), among others. Several studies question the stock market predictability on the basis that the persistence of forecasting variables and the correlation of the innovations of these variables with returns may bias the regression parameters and consequently impact their t-statistics (Stambaugh, 1999; Lewellen, 2004). Moreover, the results of this research strand contradict the weak form of the efficient market hypothesis (Fama, 1970, 1991), which states that asset prices fully and instantaneously reflect all available information so that no traders can consistently earn abnormal profits by speculating in the futures prices.[1] Another problem with the in-sample return predictability includes the use of a long list of spurious predictors such as the football results, the hemlines, and butter production in Bangladesh (e.g., Foster et al., 1997; Ferson et al., 2003; Ferreira and Santa-Clara, 2010), which have no fundamental or technical relations to stock markets. The predictability record is however not as successful in the out-of-sample forecasts. For example, Goyal and Welch (2008) find the historical mean has a better out-of-sample return predictability than the conventional predictive regressions. Therefore, the dust is not settled on the predictability of stock market returns and the jury is still out on this issue.

The actual evolution of international financial markets suggest that the economic policy uncertainty, financial stress, and consumer sentiment variables may serve as more encouraging predictors under the context of frequent crises and financial distresses. These vari-

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[1] This speculative efficiency hypothesis which involves both the spot and futures markets implies that futures prices constitute the best unbiased forecasts of future spot prices plus or minus a time-varying risk premium. Thus, speculators cannot earn abnormal profits.

ables, being related to both systematic and systemic risks, may define the stock market environment better than the traditional predictors, thereby would help to predict stock market returns over the in- and out-of-sample periods. While they convey information related to the general economic and financial conditions, their connection to stock markets and return forecastability has not been adequately investigated. With the on-going substantial volatility and financial stress in the US economy, the risk, stress and uncertainty have largely contributed to economic downturn and fluctuations in the financial markets. The rational asset pricing theory postulates that stock return predictability can emerge from exposure to time-varying aggregate risk. To the extent that successful forecasting models consistently arrest this time-varying aggregate risk premium, they will likely stay successful as time goes on. Having said all that, it is opportune to state that the predictability of stock market returns still remains an open issue and deserves more scrutiny and investigation.

The main contribution of this study is to examine the predictability of the equity premium, defined as the return on the S&P 500 (including dividends) less the return on a risk-free bill (interest rate on the three-month Treasury bill) over a monthly out-of-sample period from 2000:2 to 2011:12, using an in-sample period from 1990:2 to 2000:1 based on a more comprehensive set of economic and financial predictors. We further investigate the forecasting ability of the considered variables over the NBER-dated business-cycle expansion and recession subperiods. Compared with Rapach and Zhou (2013), we use a more updated dataset than the one used by these authors and employ four additional predictors which have not been considered in the related literature. These predictors include the US economic policy uncertainty index, the equity market uncertainty index, the University of Michigan's index of consumer sentiment, and the Kansas City Fed's financial stress index. While considering the traditional predictive variables as the baseline scenarios, our study helps to discern whether these new risk, economic policy, equity uncertainty, and consumer sentiment measures have more out-of-sample forecasting power than the traditional measures such the price multiples, firm characteristics, and macroeconomic variables. If stock market returns can be predicted more accurately after the introduction of these new predictors, the generated forecasts will not only help in the construction of relevant investment strategies in advance, but also convey important information to policymakers in order to appropriately design economic policies in order to avoid the unexpected outcomes during policy implementation phases.

Surprisingly, we find that the newly added variables do not play any significant statistical role in explaining equity premium relative to the historical average benchmark over the

out-of-sample horizon, even though these variables are believed to possess valuable informative content about the state of the economy and financial markets. Interestingly, however, barring the economic policy uncertainty index, the three other indexes considered in this study yields economically significant out-of-sample gains, especially during recessions, when compared to the historical benchmark. Even though the new indexes do not significantly forecast stock returns, the obtained results would help an investor who has access to available information on those new predictors to better forecast stock returns over the out-of-sample period, besides using the standard predictors.

The remainder of this article is organized as follows. Section 2 offers a short review of the relevant literature. Section 3 introduces the empirical methodology and forecasting evaluation criteria. Section 4 presents the data. Section 5 reports and discusses the obtained results. Section 6 concludes the article.

2. Related literature

The early literature de-emphasizes the importance of fundamentals in predicting market (excess) returns in the out-of-sample forecasts.[2] Meese and Rogoff (1983) find that predictive regressions on economic and financial fundamentals such as interest rate differentials cannot outperform the random walk approach in the out-of-sample forecasts. More recently, authors such as Burnside et al. (2007) and Burnside et al. (2008) show that buying high interest rate and shorting low interest rate currencies can produce consistent profits. Goyal and Welch (2008) investigate the out-of-sample return predictability of a long list of predictors and compare the results with forecasts from predictive regressions. These authors show that the historical mean has better out-of-sample forecasting aptitude than the traditional predictive regressions. Studies such as Inoue and Kilian (2004) and Cochrane (2008), among others, do not see this lack of success in forecastability as evidence that goes against predictability but evidence of the difficulty in obtaining successful return predictability. By using the same data that Goyal and Welch (2008) utilized and employing the sum-of-the-parts (SOP) method for 16 potential predictors, Ferreira and Santa-Clara (2011) show that the SOP approach evidently performs better than both the historical mean and the traditional predictive regressions.

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[2] Ferreira and Santa-Clara (2010) include in footnote 1 a comprehensive list of the studies and the fundamental variables that authors of these studies use over the years. The reader is advised to refer to this list, as well as to Rapach and Zhou (2013).

Recent studies offer improved forecasting techniques that provide significant out-of-sample improvements relative to the historical average benchmark. These techniques, which include economically motivated model restrictions to stabilize predictive regression forecasts (Campbell and Thompson, 2008; Ferreira and Santa-Clara, 2011), forecast combination across models, diffusion indices for tracking the key comovements in a large number of potential return predictors (Ludvigson and Ng, 2007; Kelly and Pruitt, 2012; Neely et al., 2012), and regime shifts where parameters take on different values between states (Guidolin and Timmermann, 2007; Henkel et al., 2011; Dangl and Halling, 2012), can improve forecasting performance by catering for model uncertainty and parameter instability related to the data-generating process for stock market returns (Rapach and Zhou, 2013).

Neely et al. (2012) apply a diffusion index approach to economic variables and technical indicators in order to forecast the monthly U.S. equity premium and show that generated forecasts from the diffusion index considerably outperform the historical average forecast. In a refinement of the diffusion index that relies on targeted predictors, Bai and Ng (2008) find improvements over the traditional diffusion index forecasts at all forecast horizons. Kelly and Pruitt (2012) construct a three-pass regression filter (3PRF) to estimate the factors that are the most pertinent for forecasting the target. Similarly, Kelly and Pruitt (2013) also use factors extracted from an array of disaggregated valuation ratios to produce out-of-sample U.S. equity premium forecasts that also significantly outperform the historical average forecast.

Our empirical analysis in this article also makes use of the recently developed forecasting techniques and distinguishes itself from other studies by considering predictive factors related to economic policy, equity market uncertainty, financial stress, and consumer sentiment which have become important in the aftermath of the recent global financial crisis. To the best of our knowledge, this is the first study that provides a comprehensive forecasting analysis of the US equity premium based on uncertainty, financial stress and consumer sentiment related indices.

3. Methodology

We base our analysis on the traditional predictive regression which takes the following form:

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

where r_{t+1} is the equity return premium defined as the difference between a stock return and the risk-free rate from period t to the end of period $t+1$, x_t is a lagged predictive variable available at the end of t used to predict the equity return premium, and ε_{t+1} is a zero-mean error term.

We divide the total sample of T observations for the variables r_t and x_t into an in-sample portion comprising the first n_1 observations and an out-of-sample portion made up of the last n_2 observations. A consensus has emerged amongst financial economists, which suggests that the equity premium tends to be unpredictable and, as a result, could be approximated by historical averages (Pesaran, 2003). Consequently, following Campbell and Thompson (2008) and Goyal and Welch (2008), our benchmark random walk model is defined as the historical average of the equity premium. The historical average that serves as a natural benchmark forecasting model corresponding to a constant expected equity premium is defined as follows: $\bar{r}_{t+1} = (1/t)\sum_{s=1}^{t} r_t$.

In what follows, we introduce the three improved forecasting techniques which we consider as competing models as well as the forecasting evaluation criteria. These techniques are the economically motivated model restrictions, the forecast combination method, and the diffusion index forecasting approach.

3.1 Economically motivated model restrictions

One way to improve the forecasting performance, we impose economically motivated restrictions on the predictive regression forecast of the equity premium described in Equation (1), which is

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1} \tag{2}$$

where r_{t+1} is the equity premium and the i subscript represents one of the k potential predictors ($i = 1, \dots, k$). An equity premium forecast is therefore given by

$$\hat{r}_{i,t+1} = \hat{\alpha}_{i,t} + \hat{\beta}_{i,t} x_{i,t} \tag{3}$$

where $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ are ordinary least squares estimates of α_i and β_i, respectively, based on the data from the start of the available sample through time t. Given that the out-of-sample forecast can only use data up to the time of forecast information, these parameter estimates will be less efficient than those of the in-sample period. Since there is a limited estimation

sample, and given that equity premium contains a sizable unpredictable component, it suggests that the forecasting model's parameters are potentially very imprecisely estimated. This is likely to result in poor forecasting performance. Following Rapach and Zhou (2013) and Campbell and Thompson (2008), we impose the following restrictions:

(i) If $\hat{\beta}_{i,t}$ has an unexpected sign, then $\hat{\beta}_{i,t} = 0$ when forming the forecast, and

(ii) Since risk considerations usually imply a positive expected equity premium, the forecast is equal to zero if $\hat{r}_{i,t+1} < 0$.

The imposed sign restrictions reduce the parameter estimation uncertainty and help to stabilize the predictive regression forecast. In addition to the above restrictions, we also consider the sum-of-the-parts method discussed in Ferreira and Santa-Clara (2011) and employed in Rapach and Zhou (2013). This method has shown to outperform the historical average forecasts. By definition, gross returns on a broad market index are given by:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} = CG_{t+1} + DY_{t+1} \tag{4}$$

where P_t denotes the stock price, D_t is the dividend, $CG_{t+1} = \frac{P_{t+1}}{P_t}$ is the gross capital gains and $DY_{t+1} - \frac{D_{t+1}}{P_t}$ is the dividend yield. The gross capital gain may be expressed as:

$$CG_{t+1} - \frac{P_{t+1}/E_{t+1}}{P_t/E_t} \frac{E_{t+1}}{E_t} - \frac{M_{t+1}}{M_t} \frac{E_{t+1}}{E_t} - GM_{t+1} GE_{t+1} \tag{5}$$

E_t denotes earnings, $M_t = P_t/E_t$ is the price-earnings multiple, and $GM_{t+1} = M_{t+1}/M_t$ ($GE_{t+1} = E_{t+1}/E_t$) is the gross ratio of the price-earnings multiple (earnings). Dividend yield can be written as:

$$DY_{t+1} = \frac{D_{t+1}}{P_{t+1}} \frac{P_{t+1}}{P_t} = DP_{t+1} GM_{t+1} GE_{t+1} \tag{6}$$

where $DP_t = D_t/P_t$ is the dividend-price ratio. As a result, the gross returns from Equation (4) become:

$$R_{t+1} = GM_{t+1} GE_{t+1}(1 + DP_{t+1}) \tag{7}$$

Expressed in log returns, Equation (7) becomes:

$$\log(R_{t+1}) = gm_{t+1} + ge_{t+1} + dp_{t+1} \tag{8}$$

Equation (8) is used as a basis for an equity premium forecast. To construct the sum-of-the-parts equity premium forecast, we follow Ferreira and Santa-Clara (2011) and Rapach

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and Zhou (2013). Since the price earnings multiplies and dividend-price ratios are highly persistent and almost random walks, reasonable forecasts of gm_{t+1} and dp_{t+1} based on information through t are zero and dp_t, respectively. For earnings growth, we employ a 5-year moving average of log earnings growth through t, $\overline{ge}_t^5$, since earnings growth is mostly unpredictable. The sum-of-the-parts equity premium forecast is therefore given by

$$\hat{r}_{t+1}^{sop} = \overline{ge}_t^5 + dp_t - r_{f,t+1} \tag{9}$$

The log risk-free rate is represented by $r_{f,t+1}$ and is known at the end of t. Equation (9) shows that the sum-of-the-parts forecast is a predictive regression forecast that restricts the slope coefficient to unity for $x_{i,t} = dp_t$ (log of the dividend-price ratio) and sets the intercept to $\overline{ge}_t^5 - r_{f,t+1}$.

3.2. Forecast combination methods and multiple variables predictive regression models

The forecast combination method is viewed as another approach for improving equity premium forecasts. In highlighting the importance of out-of-sample tests for evaluating equity premium predictability, Pesaran and Timmermann (1995) demonstrate the relevance of model uncertainty and parameter instability for stock return forecasting. Model uncertainty recognizes that the best model and its corresponding parameter values are generally unknown. Parameter instability suggests that the best model, if selected, can change over time. Model uncertainty and parameter instability are highly relevant for equity premium forecasting because of the connection between the business-cycle fluctuations and the equity premium predictability since these factors are also relevant to macroeconomic forecasting. The substantial model uncertainty and parameter instability surrounding the data-generating process for equity premium make the out-of-sample predictability challenging. To improve the out-of-sample equity premium based on these variables in order to address model uncertainty and also to deal with parameter instability, we rely on the combination forecast which takes the form of a weighted average of the individual forecasts, specified as

$$\hat{r}_{t+1}^{POOL} = \sum_{i=1}^{K} \omega_{i,t}\, \hat{r}_{i,t+1} \tag{10}$$

where $\{\omega_{i,t}\}_{i=1}^{K}$ are combining weights based on the information available through t and $\sum_{i=1}^{K} \omega_{i,t} = 1$. We use the simplest form of combination, i.e., the mean combination forecasting method, which sets $\omega_{i,t} = 1/K$ for all i to give the mean combination forecast.

The second combination method that we use is a discount mean square forecast error (DMSFE) which computes weights based on the forecasting performance of individual models over a hold-out out-of-sample period (see, Rapach et al., 2010; Stock and Watson, 2004 for more details).

$$w_{i,t} = \phi_{i,t}^{-1} / \sum_{j=1}^{K} \phi_{k,t}^{-1} \tag{11}$$

where

$$\phi_{i,t} = \sum_{s=m}^{t-1} \theta^{t-1-s} \left(r_{s+1} - \hat{r}_{i,s+1} \right)^2 \tag{12}$$

$m + 1$ delineates the start of the hold-out out-of-sample period, and θ is the discount factor. When $\theta = 1$, then there is no discounting and Equation (11) produces the optimal combination forecast for the case where the individual forecasts are uncorrelated. A discount factor that is less than 1 places greater importance on the recent forecasting accuracy of the individual regressions.

Following Rapach and Zhou (2013), we also look at a kitchen sink forecast. The multiple predictive regression model underlying the kitchen sink forecast is expressed as

$$r_{t+1} - \bar{r} = \sum_{i=1}^{K} \beta_i^{KS} \left(x_{i,t} - \bar{x}_i \right) + \varepsilon_{t+1}, \tag{13}$$

where $\bar{r}$ and $\bar{x}_i$ are the sample means based on data availability at the time of forecast formation for r_i and $x_{i,t}$, respectively. The kitchen sink forecast is therefore given by

$$\hat{r}_{t+1} = \bar{r} + \sum_{i=1}^{K} \hat{\beta}_i^{KS} \left(x_{i,t} - \bar{x}_i \right), \tag{14}$$

where $\hat{\beta}_i^{KS}$ is the OLS estimate of β_i^{KS} in the multiple regression of equation (13) using data available at the time of forecast formation.

We also consider the case where the multiple variables based forecasting model is selected via the Schwarz information criterion (SIC), from among 2^K possible specifications for the K=18 potential predictors, based on data available at the time of forecast formation. Since the SIC penalizes models with more parameters, the idea is to use the SIC to prevent in-sample overfitting.

3.3 Forecasting with diffusion indices

Diffusion indices have shown to provide a means for conveniently tracking key comovements in a large number of potential equity premium predictors. We follow the literature (Ludving-

son and Ng, 2007; Kelly and Pruitt, 2012; Neely et al., 2012; Rapach and Zhou, 2012; amongst others) and consider a diffusion index approach that assumes a latent factor model structure for the potential predictors:

$$x_{i,t} = \lambda_i' f_t + e_{i,t} \quad (i = 1, ..., K),$$ (15)

where f_t is a q-vector of latent factors, λ_i is a q-vector of factor loadings and $e_{i,t}$ is a zero-mean error term. To consistently estimate the latent factors, we employ the principal components technique which basically boils down to estimating:

$$r_{t+1} = \alpha_{DI} + \beta_{DI}' f_t + \varepsilon_{t+1}$$ (16)

β_{DI}' is a q-vector of slope coefficients. Equation (16) basically means that all of the k predictors potentially contain relevant information for forecasting r_{t+1}.

An equity premium forecast based on Equation (16) is given by

$$\hat{r}_{t+1}^{DI} = \hat{\alpha}_{DI,t} + \hat{\beta}_{DI,t}' \hat{f}_{t,t},$$ (17)

where $\hat{f}_{t,t}$ is the principal component estimate of f_t based on data available through to time t, while $\hat{\alpha}_{DI,t}$ and $\hat{\beta}_{DI,t}'$ are the OLS estimates of α_{DI} and β_{DI}', respectively. To select the number of factors, we rely on a procedure provided by Bai and Ng (2002) and Onatski (2010) applied to data available through time t. For forecasting, the coefficient vector q should be relatively small to avoid using an overparameterised forecasting model.

3.4 Forecast evaluation

We follow Campbell and Thompson (2008) and Rapach and Zhou (2013) and use an out-of-sample R^2 to evaluate the out-of-sample forecast, which takes the form of:

$$R_{OS}^2 = 1 - \frac{MSFE_i}{MSFE_0},$$ (20)

where $MSFE_i - \frac{1}{n_2} \sum_{s=1}^{n_2} (r_{n_1+s} - \hat{r}_{i,n_1+s})^2$ is the MSFE for the predictive regression forecast over the forecast period, with $n_2 = T - n_1$ is the out-of-sample period, n_1 is the in-sample period and $MSFE_0 = \frac{1}{n_2} \sum_{s=1}^{n_2} (r_{n_1+s} - \bar{r}_{n_1+s})^2$ is the MSFE for the historical average benchmark forecast. This means that when $R_{OS}^2 > 0$, the predictive regression forecast is more accurate than the historical average in terms of MSFE ($MSFE_i < MSFE_0$).

We further test whether the different models have a significantly lower MSFE than the benchmark historical average forecast. The null hypothesis in this case becomes $R_{OS}^2 \leq 0$ against the alternative hypothesis of $R_{OS}^2 > 0$. We use the MSFE-adjusted statistic developed by Diebold and Mariano (1995) and West (1996), which generates asymptotically valid inferences when comparing forecasts from nested linear models, and is defined as

$$DMW_i = n_2^{0.5} \bar{d}_i S_{\hat{d}_i \hat{d}_i}^{-0.5},$$

where

$$\bar{d}_i = \left(\frac{1}{n_2}\right) \sum_{s=1}^{n_2} \hat{d}_{i,m_1+s},$$

$$\hat{d}_{i,m_1+s} = \hat{u}_{0,m_1+s}^2 - \hat{u}_{i,m_1+s}^2,$$

$$\hat{u}_{0,m_1+s} = r_{n_1+s} - \bar{r}_{n_1+s},$$

$$\hat{u}_{i,m_1+s} = r_{n_1+s} - \hat{\bar{r}}_{n_1+s},$$

$$S_{\hat{d}_i \hat{d}_i} = \left(\frac{1}{n_2}\right) \sum_{s=1}^{n_2} (\hat{d}_{i,m_1+s} - \bar{d}_i)^2.$$

The DMW_i statistic is basically equivalent to the *t-statistic* corresponding to the constant for a regression of $\hat{d}_{i,m_1+s}$ on a constant for $s = 1, \dots, n_2$. This test statistic has nonstandard asymptotic distribution when comparing forecasts from nested models (Clark and McCracken, 2001; McCracken, 2007). Such nonstandard asymptotic distribution tends to result in asymptotic critical values shifting markedly to the left relative to standard normal critical values. If one bases the tests of equal predictive ability on conventional critical values, such tests tend to be severely undersized, leading to tests with very low power to detect out-of-sample return predictability. To resolve this, Clark and West (2007) propose an adjusted DMW_i statistic, $MSFE - adjusted$, for comparing nested model forecasts that have an asymptotic distribution well approximated by the standard normal. The $MSFE - adjusted$ also performs well in finite-sample simulations and is defined as:

$$\hat{d}_{i,m_1+s} = \hat{u}_{0,m_1+s}^2 - [\hat{u}_{i,m_1+s}^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2] \tag{21}$$

We then regress $\{\hat{d}_{i,n_1+s}\}_{s=1,\ldots,n_2}^{T-1}$ on a constant and calculate the t-statistics corresponding to a one-sided (upper tail) test – with the standard normal distribution.

Following the extant literature, we also analyse the predictability of equity premium using profit- or utility-based metrics which provides more direct measures of the value of forecast to economic agents. A leading utility-based metric for analysing equity premium forecasts is the average utility gain for a mean-variance investor. The first step is to compute the average utility for a mean-variance investor with relative risk aversion θ who allocates his/her portfolio between stocks and risk-free T-bills based on the equity premium predictive regression forecasts. This requires the investor to forecast the variance of the equity premium. As suggested by Campbell and Thompson (2008) and Rapach and Zhou (2013), we assume that the investor allocates the following share of his portfolio to equities during the time $t+1$

$$a_{i,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{i,t-1}}{\hat{\sigma}_{t+1}^2}\right) \tag{22}$$

where $\hat{\sigma}_{t+1}^2$ is a forecast of the variance of the equity premium, and γ is the coefficient of relative risk aversion. The average utility level realized by the investor over the out-of-sample period is given by

$$\hat{v}_i = \hat{\mu}_i - 0.5\gamma\hat{\sigma}_i^2 \tag{23}$$

where $\hat{\mu}_i$ and $\hat{\sigma}_i^2$ are the sample mean and variance of the portfolio formed on the basis of $\hat{r}_{i,t+1}$ and $\hat{\sigma}_{t+1}^2$ over the out-of-sample forecast evaluation period. If the investor instead relies on the benchmark AR(1) model of the equity premium, he allocates the portfolio share as

$$a_{0,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\bar{r}_{t+1}}{\hat{\sigma}_{t+1}^2}\right) \tag{24}$$

to equity during the time $t+1$ and he/she will realize an average utility level of

$$\hat{v}_0 - \hat{\mu}_0 - 0.5\gamma\hat{\sigma}_0^2 \tag{25}$$

where $\hat{\mu}_0$ and $\hat{\sigma}_0^2$ are the sample mean and variance over the out-of-sample period formed on the basis of $\bar{r}_{t+1}$ and $\hat{\sigma}_{t+1}^2$, respectively. The difference between Equations (23) and (25) represents the utility gain accruing to using the predictive regression forecast of the equity premium in place of the AR(1) forecast in the asset allocation decision. The utility gain is basically the portfolio management fee that an investor is willing to pay in order to have ac-

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cess to the additional information available in a predictive regression model or combination, bagging, diffusion index and Bayesian regressions relative to the information in the AR(1) model alone.

4. Data

Our study attempts to predict the US equity premium, which is measured as the difference between the return on the S&P500 total return index and the return on the risk-free three-month Treasury bill rate. As stated earlier, we use an updated version of the data used by Rapach and Zhou (2013) that is available from the website of Amit Goyal.[3] We also complement this dataset with four additional predictive variables that capture economic policy and stock market uncertainty, financial stress, and consumer sentiment: the U.S. economic policy uncertainty index, the equity market uncertainty index (EMU), the Kansas City Fed's financial stress index, and the University of Michigan's index of consumer sentiment.[4] For the uncertainty indices and the consumer sentiment, we use the logs of the indices, while for the financial stress index, we use the level. The news-based economic policy and equity market uncertainty indices are constructed on news from newspaper archives from Access World News NewsBank service (Baker et al., 2013).[5] The database of this service holds the archives of thousands of newspapers and other news sources from across the globe. The Kansas City Fed's financial stress index (KCFSI) is a measure of stress in the U.S. financial system based on eleven financial market stress-related variables (Hakkio and Keeton, 2009).[6] A positive value for this index designates that the financial stress is above the long-run average, while a negative value indicates that the stress is below the long-run average. Since the KCFSI index shoots up during crises, then another useful way to evaluate the current level of financial stress is to compare this index with its value during the past, widely acknowledged episodes of financial stress. The University of Michigan's consumer sentiment index is a level of the consumer expectations regarding the overall economy and is sourced from Thomson Reuters/University of Michigan. An improvement in this index signals that the consumers are willing to spend more on goods and service. The importance of this index is underpinned by

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[3] http://www.hec.unil.ch/agoyal/.

[4] We use the Kansas City Fed's financial stress index rather than that of the Saint Louis Fed because the former has a longer time series. The Ng and Perron (2001) unit root tests confirmed the stationarity of each of these four additional indexes. The details of these results are available upon request from the authors.

[5] This variable is available daily. We take averages of the daily data to convert it into its monthly frequency. The data is available for download from: http://www.policyuncertainty.com/index.html

[6] See http://www.kc.frb.org/research/indicatorsdata/kcfsi/ for further details regarding the index's construction.

the fact that the consumers make up close to 70% of the total economy. The variables that have been used in Goyal and Welch (2008) and in Rapach and Zhou (2013) are summarized in Table 1.

Overall, our enhanced overall monthly data starts in February 1990 and ends in December 2011. The data from 1990:02 to 2000:01 are used for the in-sample period which allows for a sixty-month rolling window for the sum-of-the-parts model, and a sixty-month hold-out period as required for the forecast combination methods. The remaining part of the sample data from 2000:02 to 2011:12 is reserved for the out-of-sample period. The starting and ending points of the dataset are purely driven by data availability of all the predictors.

Table 1: Predictive variables used in Rapach and Zhou (2013)

Predictors	Definitions
Log dividend-price ratio – Log(DP)	Log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index)
Log dividend yield – Log(DY)	Log of a 12-month moving sum of dividends minus the log of lagged stock prices
Log earnings-price ratio – Log(EP)	Log of a 12-month moving sum of earnings on the S&P 500 index minus the log of stock prices
Log dividend-payout ratio – Log(DE)	Log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings
Stock variance – SVAR	Monthly sum of squared daily returns on the S&P 500 index
Book-to-market ratio – BM	Book-to-market value ratio for the DJIA
Net equity expansion – NTIS	Ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks
Treasury bill rate – TBL	Interest rate on a three-month Treasury bill (secondary market)
Long-term yield – LTY	Long-term government bond yield
Long-term return – LTR	Return on long-term government bonds
Term spread – TMS	Long-term yield minus the Treasury bill rate
Default yield spread – DFY	Difference between BAA- and AAA-rated corporate bond yields
Default return spread – DFR	Long-term corporate bond return minus the long-term government bond return
Inflation – INFL	It is calculated from the CPI (all urban consumers); we use the lag $(t-1)$ for inflation to account for the delay in CPI releases

Table 2: Summary statistics of the variables

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB	Correlations of equity premium with the predictors
Equity premium	0.004	0.104	-0.184	0.044	-0.716	4.418	44.16[***]	-
log(DP)	-3.920	-3.239	-4.524	0.309	0.178	2.167	8.92[***]	-0.049
log(DY)	-3.915	-3.232	-4.531	0.310	0.152	2.176	8.39[***]	0.094
log(EP)	-3.147	-2.566	-4.836	0.390	-1.947	8.291	469.40[***]	-0.029
log(DE)	-0.773	1.379	-1.244	0.458	2.409	10.543	871.29[***]	-0.008
SVAR	0.003	0.057	0.000	0.005	6.487	59.331	36338.13[***]	-0.357
BM	0.281	0.522	0.121	0.091	0.339	2.558	7.14[***]	-0.073
NTIS	0.010	0.046	-0.058	0.021	-0.987	4.387	63.32[***]	0.106
TBL	0.034	0.078	0.000	0.021	-0.220	1.945	14.20[***]	0.034
LTY	0.058	0.092	0.025	0.014	0.264	2.461	6.19[***]	0.036
LTR	0.008	0.144	-0.112	0.029	-0.062	5.780	84.19[***]	-0.061
TMS	0.024	0.046	-0.004	0.014	-0.206	1.756	18.67[***]	-0.014
DFY	0.010	0.034	0.006	0.004	3.146	15.324	2082.21[***]	-0.122

DFR	-0.001	0.074	-0.098	0.016	-0.459	12.003	890.55***	0.358
INFL	0.002	0.012	-0.019	0.003	-1.201	10.121	614.16***	-0.027
EMU	4.172	6.274	2.675	0.627	0.488	3.064	10.42***	-0.214
USI	4.600	5.507	4.052	0.298	0.490	2.566	12.51***	-0.123
KCFSI	0.019	5.820	-1.080	1.028	2.680	12.842	1365.86***	-0.229
UMC	4.451	4.718	4.013	0.163	-0.635	2.760	18.19***	0.085

Notes: This table reports the summary statistics of the variables we use. A part of the variables are defined in Table 1. The market equity market premium in the United States is measured as the difference between the return on the S&P 500 total return index and the return on a risk-free three-month Treasury bill. USI, KCFSI, and UMC refer to the U.S. economic policy uncertainty index, the Kansas City Fed's financial stress index, and the University of Michigan's index of consumer sentiment. JB is the empirical statistics of the Jarque-Bera test for normality. *** indicates rejection of the normality at the 1% level.

Table 2 shows the descriptive statistics of the variables used in our predictive models. On average, the monthly level of the US market equity premium is 0.4 per cent with a standard deviation of 0.044. The KCFSI has the highest volatility amongst the variables, while the EMU is the second most volatile variable. Apart from the correlations of the equity premium with the SAVR (0.357) and the DFR (0.358), three of the additional variables, specifically KCFSI, EMU and USI, show stronger contemporaneous correlation with the US equity premium – although the correlation in general is low for all variables with the highest correlation of 0.358 for DFR and the lowest correlation of -0.014 for TMS.[7] Except log(DY), NTIS, TBL, LTY, DFR, and UMC, all other variables have a negative correlation with the equity premium. Eleven of the 18 possible predictors (including the USI and the UMC) of the equity premium have a kurtosis that is lower than the normal distribution, while the other seven have a higher than the normal distribution kurtosis. More than half of the variables are positively skewed, while the less than half are negatively skewed. All the variables do not follow the normal distribution as evidenced by the Jarque-Bera statistics since the null hypothesis that the variables are normally distributed is rejected at the 1 per cent level for all cases.

5. Results and interpretations

Table 3 reports the results obtained for the out-of-sample forecast for the unrestricted predictive regression forecasts (Panel A) and the predictive regression forecasts that implement the Campbell and Thompson (2008) sign restrictions (Panel B). We further present the results for the full sample period (1990:02 to 2011:12) and for the subperiods determined by the NBER-dated business-cycle expansions and recessions. In addition to the variables presented in Rapach and Zhou (2013), we add measures for economic policy uncertainty, financial stress,

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[7] We use the simple correlation matrix to test for correlations between variables, but we only display the correlations of the equity premium with the predictors.

and consumer sentiment to assess the role these variables play in predicting the behaviour of stock returns in the United States.

Column 2 in Panel A of Table 3 shows that only the price-dividend ratio and the dividend yield contain more information above what is contained in the historical averages. The economic policy uncertainty, equity market uncertainty, financial stress, and consumer sentiment indices are all insignificant, and the forecast combination methods (the kitchen sink, SIC, POOL-AVG, POOL-DMSFE), the diffusion index and sum-of-the-parts approaches also have statistically insignificant R_{OS}^2 at the 10 per cent level of significance. Though not perfectly comparable as we use different (smaller) in and out-of-sample periods, for the bivariate regressions, our results are in line with the findings in Rapach and Zhou (2013) and Goyal and Welch (2008), which show that individual predictive regression forecasts often fail to perform better than the historical average benchmark in terms of the means square forecast error (MSFE). This is evident since only two models (based on the price-dividend ratio and dividend yield) have a lower MSFE than the historical average. But, even though these two predictive regressions have positive R_{OS}^2, the statistic is insignificant at the 10 per cent level of significance, implying that the out-of-sample predictive ability of these variables are statistically insignificant.

When assessing the forecasting results obtained separately during expansions and recessions, the results improve only marginally. During expansions, four bivariate predictive regressions have an MSFE that is below the MSFE of the historical average, while during recessions only three variables perform better than the historical average. There is however only one bivariate model that has a statistically significant R_{OS}^2 – the dividend-price ratio during expansions. The improvement takes place despite the decrease in the number of observations used.

When comparing the results for the variables that are included in both our study and the research by Rapach and Zhou (2013), the results are generally comparable. In Rapach and Zhou (2013), for the unrestricted models and when not distinguishing between economic upswings and downswings, 12 out of 14 variables have R_{OS}^2 statistics that are negative. These results are similar to what we have, although the variables with positive R_{OS}^2 statistics differ. In Rapach and Zhou (2013), the SVAR and the TMS have positive R_{OS}^2, while in our case, the log(DP) and the Log(DY) have positive R_{OS}^2 statistics. The positive R_{OS}^2 statistic for both Rapach and Zhou's (2013) paper, and that of ours, is, however, statistically insignificant at the

10 per cent level of significance. The results of Rapach and Zhou (2013) are shown to improve when considering periods of expansion, and especially recessions. For many of the variables that have lower MSFE than the historical average, the R^2_{OS} statistics are statistically significant, with the p-values being below 10 per cent level of significance. In our case, the R^2_{OS} also improve during the expansions and the recessions, however, only two variables (dividend-price and earnings-price ratios) have significant values of R^2_{OS} at the 10 per cent level. The realized utility gains for all the variables included in the two studies show that there is a need to supplement the standard statistical criteria with more direct value-based measures when analysing the out-of-sample stock return predictability, since the utility gains contain more information than the historical averages.

Table 3: Monthly US equity premium out-of-sample forecasting results

	Panel A: without the Campbell and Thompson's (2008) economically motivated restrictions									Panel B: with the Campbell and Thompson's (2008) economically motivated restrictions								
	Overall			Expansion			Recession			Overall			Expansion			Recession		
Predictors	R_{OS}^2 (%)	p-value	Δ (ann %)	R_{OS}^2 (%)	p-value	Δ (ann %)	R_{OS}^2 (%)	p-value	Δ (ann %)	R_{OS}^2 (%)	p-value	Δ (ann %)	R_{OS}^2 (%)	p-value	Δ (ann %)	R_{OS}^2 (%)	p-value	Δ (ann %)
Bivariate regressions																		
log(DP)	0.76	0.18	-1.05	1.45	0.07	0.81	-0.39	0.50	-8.53	0.90	0.15	-0.84	1.70	0.04	1.09	-0.39	0.50	-8.53
log(DY)	1.05	0.11	-0.78	1.07	0.12	0.46	0.84	0.29	-6.24	1.29	0.07	-0.49	1.51	0.06	0.85	0.84	0.29	-6.24
log(EP)	-2.69	0.30	7.81	4.24	0.02	4.12	-12.10	0.55	22.85	2.36	0.01	7.81	1.88	0.04	4.12	3.82	0.02	22.85
log(DE)	-3.72	0.70	1.77	-2.53	0.97	-0.98	-5.96	0.59	11.34	-0.10	0.66	0.03	-0.31	0.85	-0.24	0.12	0.27	0.67
SVAR	-3.97	0.32	-2.15	-4.85	0.98	-2.12	-4.37	0.23	-2.04	-3.51	0.99	-2.56	-4.55	0.98	-2.05	-2.65	0.85	-4.81
BM	-0.22	0.55	-1.28	-0.12	0.49	-0.10	-0.07	0.48	-4.84	-0.06	0.45	-1.02	0.19	0.33	0.25	-0.07	0.48	-4.84
NTIS	-0.32	0.39	3.28	-2.23	0.96	-1.69	2.30	0.24	21.35	0.38	0.27	4.51	-0.65	0.79	-0.05	1.91	0.12	21.35
TBL	-1.69	0.64	2.14	-2.62	0.73	-1.29	-0.78	0.49	14.20	-0.05	0.41	2.16	-0.95	0.64	-1.29	1.06	0.23	14.28
LTY	-1.45	0.68	1.58	-2.86	0.86	-2.00	0.36	0.39	14.15	0.24	0.30	2.14	-0.79	0.61	-1.25	1.41	0.18	14.15
LTR	-1.11	0.98	-1.59	-0.85	0.92	-0.68	-1.24	0.92	-4.09	-0.61	0.91	-1.09	-0.55	0.84	-0.51	-0.39	0.71	-2.42
TMS	-1.38	0.99	-0.72	-2.20	0.99	-1.30	-0.52	0.75	1.16	-1.15	0.98	-0.60	-1.98	0.98	-1.21	-0.23	0.62	1.39
DFY	-3.17	0.30	4.21	-1.03	0.63	0.13	-6.16	0.27	19.80	0.53	0.23	4.58	-0.05	0.44	0.38	1.82	0.13	20.66
DFR	-4.70	0.93	-1.73	-2.03	0.84	-1.24	-9.54	0.92	-4.33	-3.24	0.88	-1.45	-1.62	0.84	-1.04	-6.07	0.82	-3.75
INFL	-1.35	0.70	-0.82	0.58	0.17	1.42	-4.08	0.92	-8.23	0.08	0.32	0.03	-0.02	0.49	0.04	0.34	0.22	0.23
EMU	-1.86	0.66	-1.28	-1.10	0.42	-1.49	-2.87	0.78	-0.20	-1.99	0.73	-1.28	-1.19	0.48	-1.49	-3.09	0.81	-0.20
USI	-1.78	0.89	-1.96	-1.46	0.98	-1.34	-2.18	0.73	-3.68	-0.94	0.93	-0.56	-1.12	0.96	-0.87	-0.67	0.72	1.05
KCFSI	-1.93	0.31	2.32	-2.42	0.95	-1.28	-1.17	0.24	15.91	0.40	0.25	3.46	-0.01	0.44	0.24	1.42	0.18	15.91
UMC	-1.44	0.73	1.08	-0.73	0.80	-0.02	-2.43	0.66	5.44	-0.32	0.69	0.72	-0.56	0.92	-0.48	0.07	0.45	5.39
Multiple variable models and forecast combination methods																		
Kitchen sink	-40.38	0.70	2.62	-23.16	0.77	-0.15	-72.91	0.66	9.98	-9.91	0.83	2.62	-16.66	0.85	-0.15	-3.42	0.66	9.98
SIC	-5.19	0.30	5.22	1.58	0.12	3.28	-16.20	0.42	13.40	-0.23	0.30	5.22	-0.94	0.36	3.28	1.04	0.31	13.40
POOL-AVG	-0.27	0.46	1.15	-0.55	0.80	-0.52	0.07	0.40	7.17	0.03	0.43	1.15	-0.55	0.80	-0.52	0.83	0.21	7.17
POOL-DMSFE	-0.27	0.45	1.33	-0.54	0.78	-0.53	0.07	0.39	8.03	0.07	0.41	1.33	-0.54	0.78	-0.53	0.93	0.19	8.03
Diffusion index	-3.71	0.81	-2.26	-0.49	0.68	-0.99	-8.70	0.80	-6.99	-0.88	0.87	-2.26	-0.49	0.68	-0.99	-1.59	0.87	-6.99
Sum-of-the-parts	-5.11	0.53	3.49	1.16	0.12	4.20	-14.64	0.78	7.11	1.01	0.08	3.49	0.71	0.16	4.20	1.37	0.17	7.11

Notes: This table summarizes the empirical results from the different forecasting models used in this study. The definition of traditional stock return predictors is given in Table 1. The equity market premium in the United States is measured as the difference between the return on the S&P 500 total return index and the return on a risk-free three-month Treasury bill rate. EMU, USI, KCFSI, and UMC refer to the equity market uncertainty index, the U.S. economic policy uncertainty index, the Kansas City Fed's financial stress index, and the University of Michigan's index of consumer sentiment. R_{OS}^2 measures the per cent reduction in mean squared forecast error (MSFE) for the predictive regression forecast based on the economic variable given in the first column relative to the historical average benchmark forecast. Column 3 reports the p-values for the Clark and West (2007) MSFE-adjusted statistic for testing the null hypothesis that the historical average MSFE is less than or equal to the predictive regression MSFE against the alternative that the historical average MSFE is greater than the predictive regression MSFE (corresponding to H_0: $R_{OS}^2 \leq 0$ against H_A: $R_{OS}^2 > 0$). The average utility gain is the portfolio management fee (in annualized per cent return) that an investor with mean-variance preferences and risk aversion coefficient of five would be willing to pay to have access to the predictive regression forecast based on the economic variable given in the first column relative to the historical average benchmark forecast. 0.00 indicates less than 0.005. The R_{OS}^2 statistics and average utility gains are computed for the entire (2000:02–2011:12) forecast evaluation period and separately for the NBER-dated expansions and recessions, and without (Panel A) and with (Panel B) the Campbell and Thompson's (2008) economically motivated restrictions.

We also report the results based on multiple economic variables with no restrictions placed on the forecasts. Though our results for the kitchen-sink model (and other multivariate models) cannot be compared with that of Rapach and Zhou (2013), primarily because we have additional variables as well as different evaluation periods, the results are generally in line with what is presented in Goyal and Welch (2008), Rapach et al., (2010) and Rapach and Zhou (2013) as the kitchen-sink method performs very poorly, compared to other models – with a R_{OS}^2 of -40.38 per cent for the overall sample period, -23.16 per cent for the expansions and -72.91 per cent for the recessions. Given the similarity of these results with those of the above-mentioned studies, tend to suggest that the kitchen-sink model do not seem to improve when equity market uncertainty, economic policy uncertainty, consumer sentiment, and financial stress indices are added to the analysis relative to the historical average. The other results based on the multiple economic variables also perform worse than the historical average when we assess the overall sample – with R_{OS}^2 ranging from -5.19 per cent (SIC) to -0.27 per cent (pool-averages and pool-DMSFE). Although the R_{OS}^2 for these models improves during the expansions and recessions, all the p-values are greater than 10 per cent, meaning that R_{OS}^2 statistics are statistically insignificant at all conventional levels.

The results for the unrestricted model in Panel A of Table 3 show that including the two uncertainty indices, the consumer sentiment, and the financial stress index (or even assessing them individually) does not yield positive forecasting gains.[8] This finding suggests that for under a linear model specification not only these variables do not seem to contain more information than that contained in the historical average, but also they are irrelevant for return forecastability despite their role in determining the macroeconomic performance. This is surprising as greater uncertainty and financial stress usually lead to increases in the equity risk premium, which, in turn, raises the cost of borrowing for firms and households as well as lower their willingness to consume. Altogether, these factors also reduce the industrial production and thereby worsen economic outlooks through affecting productivity factors, job allocation, and capital mobility.

Since the MSFE is seen as not necessarily being the most suitable metric for assessing stock returns (see Rapach and Zhou, 2013), we also take into consideration the average utility gains (annualised percentage returns) for a mean-variance investor with a relative risk coeffi-

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[8] These results are in sharp contrast with those of Rapach and Zhou (2013) who obtain significantly statistical gains under forecast combination, diffusion index and sum-of-parts methods, but under the overall scenario and the recession periods.

cient of five who allocates his/her investments between equities and risk-free bills, using predictive regression forecasts instead of relying on historical average. The utility gains results for the unrestricted predictive regression forecasts are reported in column 3 for the overall sample, column 6 for the expansions and column 9 for the recessions. Compared to the R_{OS}^2, the predictive regression forecasts appear to be significantly more valuable when looking at the average utility gains. For the overall sample, eight of the predictive regression forecasts exhibit positive utility gains, which also includes the financial stress (2.32 per cent) and consumer sentiment (1.08) indices.[9] The positive utility gains are all above 1 per cent, meaning that investors are willing to pay above 100 basis points to have access to the information in the predictive regression forecasts compared to the historical averages. On the other hand, the economic policy uncertainty experiences a negative utility gain (-1.96), meaning that investors have no interest in paying for such kind of information when making return forecasts. Contrary to the pattern observed with the R_{OS}^2, the utility gains are much higher during recessions than expansions and the uncertainty and stress indices do not seem to play any role during expansions. The utility gains for the KCFSI increase from 2.32 per cent for the overall sample to 15.90 per cent during recessions, while they rise to 5.44 per cent for the UMC index. The utility gains for the different types of the out-of-sample periods provide stronger support for equity premium forecastability compared to the R_{OS}^2.[10] This highlights the need to supplement standard statistical criteria with more direct value-based measures when analysing out-of-sample equity premium predictability. Most importantly, information contained in the financial stress index and the consumer sentiment should not be ignored and investors should take them into consideration when predicting stock returns in the United States.

For the multivariate models, there are high utility gains, especially for the recessions. The SIC outperforms all other models during recessions (5.22 per cent for the overall sample and 13.40 per cent during recessions) and is second best during expansion periods (3.28); only the diffusion index has negative utility gains for the overall sample and during recessions, suggesting that this model persistently performs poorly than the historical average despite business cycle movements.[11]

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[9] In Rapach and Zhou (2013), 10 of the predictors were shown to have positive utility gains, which of course did not include our four additional predictors.

[10] Rapach and Zhou (2013) also obtained similar results in the sense that not only did the number of predictors producing utility gains went up from 7 under expansions to 12 under recessions, the magnitude of the gains was also larger.

[11] These results involving utility gains are, in general, similar to those of Rapach and Zhou (2013).

We further report the R_{OS}^2 and the utility gains for predictive regression forecasts that impose the Campbell and Thompson (2008) sign restrictions (Panel B). Imposing sign restrictions marginally improves the results relative to those without restrictions – a finding also observed in Rapach and Zhou (2013). For the overall sample, now eight of the predictive regression forecasts perform better than the historical average. Imposing nonnegative restrictions improved the performance of the KCFSI, although it is the only index that we included that performs better than the historical average, with a R_{OS}^2 of 0.4 per cent. The R_{OS}^2 is however statistically insignificant as it has a p-value that is above the 10 per cent. Only log(DY) and log(EP) have statistically significant R_{OS}^2. The results for the log(DP), log(DY) and log(EP) improve during expansions, with statistically significant R_{OS}^2. Although the R_{OS}^2 seem small, the values still represent equity premium predictability from the standpoint of leading asset pricing models, making them statistically relevant. Most of the uncertainty indices perform worse than the historical average during the different sample periods. Only the KCFSI has a lower MSFE than the historical average, although the R_{OS}^2 remains statistically insignificant during the overall sample and during the recession, since the p-values are above 10 per cent. When using the MSFE, the information contained in the uncertainty indices seems to be minimal. As in Rapach and Zhou (2013), our results for the utility gains seem to be marginally affected by the restrictions we imposed on the models. Although more models with multiple economic variables perform better than the historical average at different forms (overall, expansions and recessions) of the sample periods, the R_{OS}^2 values remain statistically insignificant, while the utility gains for these models remain relatively unchanged from the unrestricted models' results presented in Panel A.[12]

6. Conclusions

This article investigates the predictability of the US equity premium, defined as the return on the S&P 500 total return index minus the return on a risk-free bill (interest rate on the three-month Treasury bill) over a monthly out-of-sample period of 2000:2 to 2011:12, using an in-sample of 1990:2-2000:1 based on a comprehensive set of 18 predictors, accounting for both

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[12] With the focus of the paper being predictability of US equity premium based on policy and market uncertainty, financial stress and consumer sentiment indices, we checked for the robustness of the multivariable results presented in Table 3 by completely dropping the four indices, including the four indices one at a time, various combinations of two and three of the indices at a time. Our results reported in Table 3 were qualitatively unaffected. The robustness analyses have been suppressed for the sake of brevity, but complete details are available upon request from the authors.

expansion and recession phases over the out-of-sample horizons, besides the overall out-of-sample period. Besides the widely used predictors in the extant literature (see Rapach and Zhou, 2013 for further details) on equity premium predictability, our study includes four new predictors related to rising policy and market uncertainty and financial stress due to the lingering effect of the recent global financial crisis and the Great Recession in the United States. Those new predictors are the U.S. economic policy and equity market uncertainty indices, the Kansas City Fed's financial stress index and University of Michigan's index of consumer sentiment. Relying on predictive regression frameworks that also include economically motivated restrictions, the diffusion index and sum-of-parts approaches as well as forecast combination methods, the additional predictors do not play any significant statistical role in explaining equity premium relative to the historical average benchmark over the out-of-sample horizon, even though they are believed to possess valuable informative content about the state of the economy and financial markets. Interestingly however, barring the economic policy uncertainty index, the three other indices considered in this study yields economically significant out-of-sample gains, especially during recessions, when compared to the historical benchmark. Overall, our results indicate that three of the four indices are economically, but not statistically, significant in forecasting US equity premium. In light of this poor statistical forecasting performance of these four indices, future research should concentrate on forecasting with the multivariate model using Bayesian shrinkage (Gupta et al., 2013), or even perhaps using regime-switching (Guidolin and Timmermann, 2007), time-varying (Dangl and Halling, 2012) and nonparametric (Chen and Hong, 2010) models, since Rapach and Wohar (2006) provide strong evidence of the existence of structural breaks in the relationship between US stock returns and the predictors (both in bivariate and multivariate settings), which is also likely to be the case with our four additional predictors

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