

Goodness C. Aye

Department of Economics,
University of Pretoria,
South Africa

✉ goodness.aye@gmail.com

Frederick W. Deale

Department of Economics,
University of Pretoria,
South Africa

✉ dealed@lantic.net

Rangan Gupta

Corresponding author

Department of Economics,
University of Pretoria,
South Africa

✉ rangan.gupta@up.ac.za

Does Debt Ceiling and Government Shutdown Help in Forecasting the US Equity Risk Premium?

Summary: This article evaluates the predictability of the equity risk premium in the United States by comparing the individual and complementary predictive power of macroeconomic variables and technical indicators using a comprehensive set of 16 economic and 14 technical predictors over a monthly out-of-sample period of 1995:01 to 2012:12 and an in-sample period of 1986:01-1994:12. In order to do so we consider, in addition to the set of variables used in Christopher J. Neely et al. (2013) and using a more recent dataset, the forecasting ability of two other important variables namely government shutdown and debt ceiling. Our results show that one of the newly added variables namely government shutdown provides statistically significant out-of-sample predictive power over the equity risk premium relative to the historical average. Most of the variables, including government shutdown, also show significant economic gains for a risk averse investor especially during recessions.

Key words: Equity risk premium forecasting, Debt ceiling, Government shutdown, Out-of-sample forecasts, Asset allocation.

JEL: C38, C53, C58, E32, G11, G12, G17.

Predictability of equity risk premium is still one of the on-going questions being debated by practitioners and researchers. This is because accurate prediction of the equity risk premium is central to risk and return models since it affects expected returns of risky investments. Aswath Damodaran (2013) also noted that it plays a key role in estimating cost of equity and capital in corporate finance and valuation.

The widely used macroeconomic and technical predictors may not adequately capture the dynamics of the equity risk premium. As a result, researchers continue to seek for predictors that may help explain the equity market. This study considers two new variables namely the government shutdown and debt ceiling which have not been previously used in any empirical research to our knowledge.

Overall, market participants react to news, hence protracted debate about the debt ceiling and government shutdown could cause market participants to lose confidence in the United States' willingness to pay its bills and fund important operations and obligations. This could spark renewed financial market stress, a fall in stock prices and wider credit spreads consequently depressing private sector spending since about half of the U.S. households own stocks through mutual funds or 401(k) ac-

counts (U.S. Department of the Treasury 2013). Further, increased uncertainty or reduced confidence could lead consumers to postpone purchases and businesses to postpone hiring and investments and these would lead to weaker economic expansion (U.S. Department of the Treasury 2013).

Against this background, this article evaluates the out-of-sample predictive ability of the government shutdown and debt ceiling in addition to other economic variables and technical indicators to predict the equity risk premium in the United States. This is done by regressing the equity risk premium on a constant and the lag of either a macroeconomic variable or a technical indicator. We also estimate predictive regression based on the extracted principal components for both the economic variables and the technical indicators individually and combined.

For the remainder of the paper the structure is as follows: Section 1 presents the literature review. Section 2 shows the methodology used as well as the forecasting evaluation criteria. The data is presented in Section 3 while the empirical findings are discussed in Section 4 whilst Section 5 concludes.

1. Literature Review

Prior to the mid-1980's it was believed that equity returns are unpredictable (John H. Cochrane 1999) after which the consensus became that some variables can have predictive power over future movements in stock prices (John Y. Campbell 1999, 2000). Macroeconomic variables became important in predicting future expected equity returns as the future state of the economy functions as a key driver in dynamic asset pricing models (David E. Rapach and Guofu Zhou 2013). There have been numerous studies that have dealt with the predictability of the US equity risk premium based on different economic and financial predictors and methodologies (Rangan Gupta et al. 2013).

In the vast literature there has been evidence of numerous economic variables, including nominal interest rates, interest rate spreads, valuation ratios, book to market ratios, the inflation rate and more which could be possible predictors of the equity premium (Rapach, Jack K. Strauss, and Zhou 2010). Dividend ratios and dividend yields could be robust predictors of the equity premium as suggested by Amit Goyal and Ivo Welch (2003), and Cochrane (2008) and studies such as those done by Rapach and Mark E. Wohar (2005) show that price dividend and price-earnings ratios can predict real future equity returns. The majority of these studies find strong support for in-sample predictive ability but generally poor performance for the same models when testing out-of-sample predictive power.

The studies of technical indicators attempt to identify price and/or volume patterns that practitioners often use as they are believed to persist in the future (for a brief survey on popular technical indicators see Neely et al. 2013). The majority of studies aim to analyse the profitability of applying technical indicators in trading strategy while few analyse their ability to predict the equity risk premium. Neely et al. (2013) finds that technical indicators have predictive power that are economically significant both in- and out-of-sample that either outperforms or matches that of macroeconomic variables especially near business cycle peaks where the equity risk premium usually declines. They also find that the technical indicators and macroeco-

conomic variables behave complimentary when it comes to predicting the equity risk premium.

Spurious regression bias that can be a result of trending levels of independent time series and mining data for predictors can also be a serious problem as the two effects reinforce each other (Wayne E. Ferson, Sergei Sarkissian, and Timothy T. Simin 2003). Explanations for the behaviour of the in-sample forecasting predictability are generally attributed to specific factors related to the market microstructure such as transaction costs, heterogeneity amongst agents and information asymmetry (Gupta et al. 2013). More importantly, out-of-sample forecasts fail in comparison to the historical average using standard predictive regression (Welch and Goyal 2008) and asset pricing models fail to deliver out-of-sample forecasts compared to a constant benchmark (Simin 2008). It is a clear trend in more recent literature to focus on the out-of-sample predictive ability compared to the historical average, which Goyal and Welch (2003), Welch and Goyal (2008) showed to be a very stringent out-of-sample benchmark, and has been used by many other studies including Campbell and Samuel B. Thompson (2008) and Miguel A. Ferreira and Pedro Santa-Clara (2011).

From the foregoing, it is clear that the forecasting ability of many macroeconomic and technical variables for equity risk premium has been tested. However, the current study contributes by testing the forecasting ability of two new variables namely government shut down and debt ceiling for the US equity risk premium. These two are used in addition to the commonly used predictors in the literature. We evaluate the out-of-sample predictability of the equity risk premium during expansions and recessions following the National Bureau of Economic Research (NBER) - dated business cycle and the possible CER gains for a risk averse investor.

2. Methodology

In our analysis we follow the same methodology as in Neely et al. (2013). This involves a traditional bivariate predictive regression approach which is discussed in Section 2.1 and is done for the economic variables and the technical indicators. Following that, predictive regression based on principal components, which is discussed in Section 2.2, is done for the economic variables and technical indicators individually as well as combined. We present the out-of-sample forecast evaluation criterion in Section 2.3.

2.1 Bivariate Predictive Regression

The predictive regression model for analysing the equity risk premium using macroeconomic variables as predictors takes the following form:

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

where r_{t+1} is the equity risk premium, defined as the return on the broad stock market index in excess of the risk free rate from period t to $t+1$, $x_{i,t}$ is the economic predictor variable at period t and $\varepsilon_{i,t+1}$ is the zero mean error term at time period $t+1$.

We use the same 14 technical indicators which are based on three popular trend following strategies as used by Neely et al. (2013) to generate trading rules. In

order to compare the technical indicators predictive ability with that of the macroeconomic variable's the rules generate buy signals where $S_{it} = 1$ and sell signals where $S_{it} = 0$. The first rule is a moving average (MA) rule that generates its signal by comparing two moving averages:

$$S_{i,t} = \begin{cases} 1 & \text{if } MA_{s,t} \geq MA_{l,t} \\ 0 & \text{if } MA_{s,t} < MA_{l,t} \end{cases} \tag{2}$$

where:

$$MA_{j,t} = \left(\frac{1}{j}\right) \sum_{i=0}^{j-1} P_{t-i} \text{ for } j = s, l; \quad s < l \tag{3}$$

where P_t is defined as the level of the stock price index at period t , s and l are the lengths of the short and long MA's respectively. Because the short MA will be more sensitive to recent movements in price than the long MA the rule detects changes in price trends for the stock index. We analyse monthly MA rules with $s = 1, 2, 3$ and $l = 9, 12$ as in Neely et al. (2013).

The second strategy rule is based on momentum and gives us the following signal:

$$S_{i,t} = \begin{cases} 1 & \text{if } P_t \geq P_{t-m} \\ 0 & \text{if } P_t < P_{t-m} \end{cases} \tag{4}$$

If the current price of the stock index P_t is higher than it was m periods ago at P_{t-m} it has relatively high expected excess returns which is indicative of positive momentum which generates a buy signal. The momentum indicator is denoted by $MOM(m)$ with monthly signals of $m = 9, 12$ thus we compare today's stock index price with that of 9 months ago and 1 year ago respectively.

Volume data combined with past prices is frequently used in practice to identify trends. Therefore, our final strategy incorporates "on-balance" volume (OVB) (e.g. Neely et al. 2013). Firstly we define:

$$OBV_t = \sum_{k=1}^t VOL_k D_k, \tag{5}$$

where VOL_k measures the trading day volume during the period k . D_k is a binary variable which is equal to one if $P_k - P_{k-1} \geq 0$ and 1 otherwise. The trading signal $S_{i,t}$ is then formed from OBV_t such that:

$$S_{i,t} = \begin{cases} 1 & \text{if } MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0 & \text{if } MA_{s,t}^{OBV} < MA_{l,t}^{OBV} \end{cases} \tag{6}$$

where:

$$MA_{j,t}^{OBV} = \left(\frac{1}{j}\right) \sum_{i=0}^{j-1} OBV_{t-i} \text{ for } j = s, l. \tag{7}$$

Relatively higher recent volume in combination with recent rises in the price level of the stock index indicates a strong positive market trend which should indicate a buy signal and *vice versa*. As in Neely et al. (2013) we also compute monthly signals for $s = 1, 2, 3$ and $l = 9, 12$ where the notation is $VOL(s, l)$. The technical indicators are then transformed to point forecasts of the equity risk premium by replacing $x_{i,t}$ in (1) with $S_{i,t}$ from (2), (4) or (6) respectively which gives us:

$$r_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}. \quad (8)$$

This enables us to compare these newly created technical indicators to the forecasts of the equity risk premium based on the macroeconomic variables as $S_{i,t}$ creates either a bullish or a bearish signal where it is 1 and 0 respectively.

2.2 Predictive Regression Based on Principal Components

By estimating predictive principal component models we incorporate all the information of multiple variables in one model. We estimate a model for macroeconomic variables (PC-ECON), technical indicators (PC-TECH) and a combined model (PC-ALL) which parsimoniously incorporates information from our entire set of variables. For the PC-ECON model let $x_t = (x_{1,t}, \dots, x_{N,t})'$ denote the N-vector of the entire set of macroeconomic variables where $N_{econ} = 16$ and let $\hat{F}_t^{Econ} = (\hat{F}_{1,t}^{Econ}, \dots, \hat{F}_{K,t}^{Econ})'$ denote the vector which contains the first K principal components extracted from x_t where $K < N$. The PC-ECON predictive regression which can be estimated using OLS is then given by:

$$r_{t+1} = \alpha + \sum_{k=1}^K \beta_k \hat{F}_{k,t}^{Econ} + \varepsilon_{t+1}. \quad (9)$$

By using the K-vector $\hat{F}_t^{Tech} = (\hat{F}_{1,t}^{Tech}, \dots, \hat{F}_{K,t}^{Tech})'$ which contains the first K principal components extracted from $S_t = (S_{1,t}, \dots, S_{N,t})'$ with $N_{tech} = 14$ we can have a similar predictive regression based on principal components (PC-TECH) extracted from the technical indicators given by:

$$r_{t+1} = \alpha + \sum_{k=1}^K \beta_k \hat{F}_{k,t}^{Tech} + \varepsilon_{t+1}. \quad (10)$$

For the PC-ALL predictive model we use the K-vector $\hat{F}_t^{All} = (\hat{F}_{1,t}^{All}, \dots, \hat{F}_{K,t}^{All})'$ which contains the first K principal components extracted from $z_t = (x_t', S_t')'$ which is the $(N_{econ} + N_{tech}) = 30$ vector containing all 16 macroeconomic variables and all 14 technical indicators. The PC-ALL model which can be estimated using OLS is given by:

$$r_{t+1} = \alpha + \sum_{k=1}^K \beta_k \hat{F}_{k,t}^{All} + \varepsilon_{t+1}. \quad (11)$$

2.3 Out-of-Sample Forecast Evaluation

We use 1986:01 to 1994:12 as our initial estimating period and have 1995:01 to 2012:12 as our forecast evaluation period. We compute similar statistics as Neely et al. (2013) which tests all of our models with the crucial difference being differences in our in-sample period and out-of-sample period because of differences in the time period of the data. The reason we start the out-of-sample evaluation period at 1995 are because there were spikes in the equity risk premium and our newly included variables near that period indicating that their performance would be best tested from that time period. The out-of-sample period is relatively large in proportion to the sample as this enables us to have better size properties as shown by Peter R. Hansen and Alan Timmermann (2012). For the month-($t+1$) out-of-sample equity risk premium forecast based on the individual macroeconomic variables as in (1) with data through month t then we have:

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i}x_{i,t}, \tag{12}$$

where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the OLS estimates from regressing $\{r_s\}_{s=2}^t$ on a constant and $\{x_{i,s}\}_{s=1}^{t-1}$. The out-of-sample forecast based on individual technical indicators as in (8) is given by:

$$\hat{r}_{t+1} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i}S_{i,t}, \tag{13}$$

where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the OLS estimates from regressing $\{r_s\}_{s=2}^t$ on a constant and $\{S_{i,s}\}_{s=1}^{t-1}$. Finally, the out-of-sample forecasts based on principal components as in (9), (10) and (11) is generated by:

$$\hat{r}_{t+1}^j = \alpha + \sum_{k=1}^K \hat{\beta}_{t,k} \hat{F}_{1t,k,t}^j \quad \text{for } j = ECON, TECH, ALL \tag{14}$$

where $\hat{F}_{1t,k,t}^j$ is the k^{th} principal component extracted either from the 16 macroeconomic variables for $j = ECON$, the 14 technical indicators for $j = TECH$ or all of the macroeconomic variables and the technical indicators combined for $j = ALL$ based on data through t . $\hat{\alpha}_t$ and $\hat{\beta}_{t,k}$ are the OLS estimates from regressing $\{r_s\}_{s=2}^t$ on a constant and $\{\hat{F}_{1t,k,t}^j\}_{s=1}^{t-1}$ for $k = 1, \dots, K$ and K is selected on the adjusted R^2 based on data through t . The forecasts are generated using a recursive window for estimating α_i and β_i in (1).

We then compare the forecasts from (12), (13) and (14) to the historical average as given by:

$$\hat{r}_{t+1}^{Ha} = \left(\frac{1}{t}\right) \sum_{s=1}^t r_s, \tag{15}$$

which has been shown by Goyal and Welch (2003), and Welch and Goyal (2008) to

be a very good out-of-sample benchmark for the equity premium. To analyse the forecasts we use Todd E. Clark and Kenneth D. West (2007) mean square forecast error (MSFE)-adjusted statistics calculated from the Campbell and Thompson (2008) out-of-sample \bar{R}^2 denoted by R_{OS}^2 which measures the proportional reduction in the MSFE for the predictive regression forecasts relative to the historical average (Neely et al. 2013) and takes the form of:

$$R_{OS}^2 = 1 - \frac{MSFE_t}{MSFE_0}, \quad (16)$$

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

We also employ the MSFE-adjusted statistic proposed by Clark and West (2007) which is an adjustment of the well-known Diebold-Mariano/West (DMW_i) statistic developed by Francis X. Diebold and Roberto S. Mariano (1995) and West (1996) and used in numerous other similar recent studies including Rapach, Strauss, and Zhou (2010), Aiguo Kong et al. (2011), Gupta et al. (2013) and Neely et al. (2013). The adjustment resolves difficulties of the original method when comparing nested model forecasts that have asymptotic distributions which are well approximated by the standard normal distribution. The null hypothesis of this test becomes $R_{OS}^2 \leq 0$ with the alternative being $R_{OS}^2 > 0$. The original DMW_i statistic is given by:

$$DMW_i = n_2^{0.5} \bar{d}_i \hat{S}_{d_i, d_i}^{-0.5}, \quad (17)$$

where:

$$\bar{d}_i = (1/n_2) \sum_{s=1}^{n_2} \hat{d}_{i,n_1+s}, \quad (18)$$

$$\hat{d}_{i,n_1+s} = \hat{u}_{0,n_1+s}^2 - \hat{u}_{i,n_1+s}^2, \quad (19)$$

$$\hat{u}_{0,n_1+s}^2 = r_{n_1+s} - \bar{r}_{n_1+s}, \quad (20)$$

$$\hat{u}_{i,n_1+s}^2 = r_{n_1+s} - \hat{r}_{n_1+s}, \quad (21)$$

$$\hat{S}_{d_i, d_i} = (1/n_2) \sum_{s=1}^{n_2} (\hat{d}_{i,n_1+s} - \bar{d}_i)^2. \quad (22)$$

The t -statistic corresponding to the constant for a regression of \hat{d}_{i,n_1+s} on a constant for $s = 1, \dots, n_2$ is equivalent to the DMW_i statistic. The MSFE-adjusted statistic can be computed by defining:

$$\tilde{d}_{i,n_1+s} = \hat{u}_{0,n_1+s}^2 - [\hat{u}_{i,n_1+s}^2 - (\bar{r}_{n_1+s} - \hat{r}_{i,n_1+s})^2], \tag{23}$$

and then regressing \tilde{d}_{i,n_1+s} on a constant for $s = 1, \dots, n_2$. The t -statistic corresponding to the constant is now the MSFE-adjusted statistic.

We further analyse the predictability of the equity risk premium using the same methodology of utility based metrics as Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), and Neely et al. (2013) where we compute the certainty equivalent return (CER) for an investor with mean-variance preferences who allocates between equities and risk-free bills each month using various equity risk premium forecasts. This is done to incorporate risk aversion into an investor’s allocation decision where a risk averse investor takes into consideration how many securities would reduce the risk of their portfolio (Dragana M. Đurić 2006). Because the investor is allocating between the stock market index and the risk free bonds we do not expect the diversification benefits to disappear during periods of turmoil as it could if allocating between different international stock markets (Cristiana Tudor 2011). At the end of month t the investor will optimally allocate the following share w_t of his whole portfolio towards equities during month $t + 1$ and $1 - w_t$ is allocated towards risk-free bills.

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

where \hat{r}_{t+1} is a forecast of the equity risk premium and $\hat{\sigma}_{t+1}^2$ is a forecast of its variance which is, as in Neely et al. (2013) and Campbell and Thompson (2008) estimated assuming the investor uses a five-year moving window of past monthly returns.

w_t is assumed to lie between 0 and 1.5 which imposes a realistic constraint on the portfolio that short selling is precluded and the maximum leverage is 50%. The portfolio returns for month $t + 1$ is given by:

$$R_{p,t+1} = w_t r_{t+1} + R_{f,t+1}. \tag{25}$$

The CER for the portfolio is:

$$CER_p = \hat{u}_p - \frac{1}{2} \gamma \hat{\sigma}_p^2, \tag{26}$$

where \hat{u}_p and $\hat{\sigma}_p^2$ are the mean and variance for the investor’s portfolio over the forecast period respectively. The certainty equivalent return (CER) gain is the difference between the CER for an investor who uses one of the predictive regression forecasts based on principal components and the CER for an investor who uses the historical

average. This difference is multiplied by 1200 to be interpreted as the annual percentage portfolio management fee that an investor would be willing to pay to use the predictive regression forecast instead of the historical average.

When we evaluate the out-of-sample forecasts during NBER-dated business-cycle expansions and recessions, we compute R_{os}^2 and CER statistics for cyclical expansions and recessions separately.

3. Data

For our analysis we use the same variables and data as the previous study by Neely et al. (2013) and included two economic variables namely government shutdown and debt ceiling. On one hand, government shutdown in the United States politics is the name for the process the Executive Branch must enter into, when the Congress creates a “funding gap” by choosing not to or failing to pass legislation funding government operations and agencies (Clinton T. Brass 2011). Prior to 1980, a funding gap did not lead to government shutdown until when Attorney General Benjamin Civiletti issued a legal opinion that all government work must stop if Congress does not agree to pay for it but later opined that essential government services should be allowed to continue in the absence of a spending bill (Connie Cass 2013; Scott Horsley 2013). This also usually results in the cessation or reduction of federal employees. On the other hand, the debt ceiling is part of a law created by Congress which does not control or limit the ability of the federal government to run further deficits or incur obligations, but it is a limit on the ability to pay obligations already incurred (Government Accountability Office 2011). It is argued that delays in payment may ensue if debt ceiling is not raised and this would lead to default on government debt (Carol E. Lee and Janet Hook 2013). These two variables are measured in this study as the frequency of mention of “debt ceiling” or “government shutdown” as a percentage of total news articles from Access World News’ Newsbank Service which contains relevant archives of over 1000 US newspapers differing in size.

The reactions in the financial markets suggest that the government shutdown and debt ceiling may have valuable predictive power on the equity risk premium and contain important information about the state of the economy. The debt ceiling and government shutdown, although closely related, should affect the equity risk premium through different channels. In the US the occurrence, costliness and intensity of government shutdowns are increasing (Katharine Young 2014). Intuitively, during a government shutdown the risk free rate will remain the same because there is no added risk of default of the US government. There is added risk of policy uncertainty and deteriorating public trust (Young 2014) which can feed through to overall risk of an equity investment and thus influence the equity risk premium (Damodaran 2013). Reaching the debt has not happened before but the consequences of it being reached would most likely result in a default on some debt obligations of government such as non-payment of interest on bonds. During the 2011 debt ceiling debate there was a large spike in economic uncertainty (Scott R. Baker, Nicholas Bloom, and Steven J. Davis 2013). A large spike in economic uncertainty might not have predictive power per se (Gupta et al. 2013) but could lead to delayed investment or consumption of

durables (Baker, Bloom, and Davis 2013) or damage to the reliability of the US as a borrower shown by warnings of downgrades from multiple ratings agencies. There is thus an increasing possibility of default on the US government securities (Srinivas Nippani and Stanley D. Smith 2010). An increase in their default risk would most likely result in a decrease in the equity risk premium *ceteris paribus*. Because of their different feedback effects, it is important to model them separately and not use a proxy that combines the two variables.

The 16 economic variables used for analysis are defined in Table 1. Apart from government shutdown and debt ceiling, the rest variables are from Neely et al. (2013). However, Book-to-market ratio is originally from Welch and Goyal (2008). The technical variables are created in a similar fashion as Neely et al. (2013) using S&P 500 index and monthly volume data from Google Finance for our time period. The technical indicators indicate buy signals between 73% and 77% of the time for our timeframe.

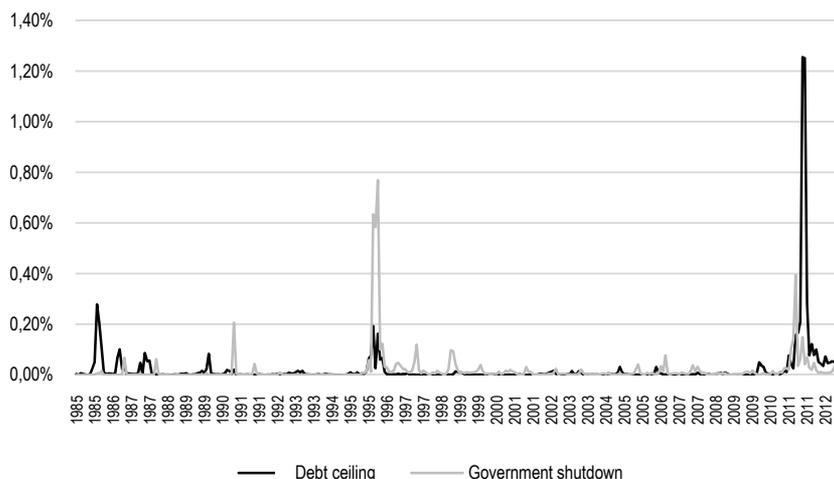
Table 1 Predictive Economic Variables Used for Analysis

Predictors	Definitions
Log dividend-price ratio - DP	Log of a twelve-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 - DY	Log of a twelve-month moving sum of dividends minus the log of lagged stock prices.
Log earnings-price ratio - EP	Log of a twelve-month moving sum of earnings on the S&P 500 index minus the log of stock prices.
Log dividend-payout ratio - DE	Log of a twelve-month moving sum of dividends minus the log of a twelve-month moving sum of earnings.
Equity risk premium volatility - RVOL	Twelve-month moving sum of earnings.
Book-to-market ratio - BM	Based on a twelve-month moving standard deviation estimator (Antonio Mele 2007).
Net equity expansion - NTIS	Ratio of a twelve-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 Moody's 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	Calculated from the CPI for all urban consumers; we use the lag (t-1) for inflation to account for the delay in CPI releases.
Debt ceiling - DEBTCEIL	The number of mentions of "debt ceiling" as a percentage of total news articles from Access World News' Newsbank Service.
Government shutdown - GOVSHUT	The number of mentions of "government shutdown" as a percentage of total news articles from Access World News' Newsbank Service.

Source: Authors' definitions.

The data on debt ceiling and government shutdown is based on the number of mentions of "debt ceiling" or "government shutdown" as a percentage of total news

articles from Access World News' Newsbank Service which contains relevant archives of over 1000 US newspapers differing in size. It has been calculated from January 1985 until September 2013, which is the shortest time period of all of our predictors, and serves as the starting and ending point of the entire dataset. There are large spikes in the number of mentions of these terms whenever there are either talks or occurrences of government shutdown or talks about the debt ceiling. In most years there is however only sporadic mentions of these terms as shown by Figure 1. Both series are sourced from the policyuncertainty.com database (Economic Policy Uncertainty 2014)¹.



Source: Authors' plots based on data obtained from Economic Policy Uncertainty (2014).

Figure 1 Plot of Debt Ceiling and Government Shutdown

Table 2 reports the descriptive statistics of the economic variables used in our predictive models. The average monthly US market equity risk premium is 0.48%, the standard deviation 4.57 and subsequently the Sharpe ratio of 0.10. Most of the macroeconomic variables are strongly autocorrelated, with 11 autocorrelation values above 0.9 and only 4 below 0.5, our newly added variables DEBTCEIL and GOVSHUT also shows some autocorrelation with values of 0.67 and 0.61 respectively. The newly added variables also have relatively strong correlation with the equity premium with DEBTCEIL at -0.068 and GOVSHUT at 0.073 which are stronger than all but 3 other economic variables correlations namely DFR (0.254), DFY (-0.082) and DY (0.096) and the lowest correlation is that of INFL (0.001). The very low volatility that DEBTCEIL and GOVSHUT show can be attributed to the measurement methodology of the data which only measures them as percentage of all newspaper reports. None of the variables follow a normal distribution as shown by

¹ **Economic Policy Uncertainty.** 2014. Economic Policy Uncertainty Index. www.policyuncertainty.com (accessed January 15, 2014).

the Jarque-Bera statistics since the null hypothesis that the variables follow a normal distribution is rejected at a 1% level for all variables but RVOL and LTY which are rejected at a 5% level of significance.

Table 2 Summary Statistics 1986:01 to 2012:12

Variable	Mean	Std. dev	Min	Max	JB	Autocorrelation	Correlation of equity premium with the predictors
Log equity premium	0.48	4.57	-24.84	12.22	221.50***	0.07	
DP	-3.84	0.33	-4.52	-3.24	16.26***	0.99	-0.041
DY	-3.83	0.33	-4.53	-3.23	15.65***	0.99	0.096
EP	-3.06	0.40	-4.84	-2.46	525.52***	0.98	-0.021
DE	-0.78	0.42	-1.24	1.38	1451.20***	0.98	-0.013
RVOL	0.15	0.06	0.05	0.32	7.59**	0.96	0.031
BM	0.31	0.11	0.12	0.58	11.02***	0.98	-0.052
NTIS	0.01	0.02	-0.06	0.05	17.12***	0.98	0.050
TBL(ann%)	3.79	2.36	0.01	8.82	14.28***	1.00	0.026
LTY(ann%)	6.14	1.82	2.06	9.92	7.42**	0.99	0.005
LTR(%)	0.79	2.99	-11.24	14.43	67.35***	0.02	-0.017
TMS(ann%)	2.35	1.32	-0.41	4.55	19.30***	0.97	-0.041
DFY(ann%)	1.00	0.40	0.55	3.38	2371.47***	0.96	-0.082
DFR(%)	-0.03	1.64	-9.75	7.37	740.39***	0.00	0.254
INFL(%)	0.23	0.32	-1.92	1.22	660.16***	0.46	0.001
DEBTCEIL	0.00	0.00	0.00	0.01	218315.30***	0.67	-0.068
GOVSHUT	0.00	0.00	0.00	0.01	71220.62***	0.61	0.073

Notes: This table reports the rounded summary statistics of the log equity risk premium which is measured as the difference between the total return on the S&P 500 index and the return on the risk free three-month Treasury bill, the debt ceiling (DEBTCEIL) and the government shutdown (GOVSHUT) which are measured as the number of mentions of each of these terms in Access World NewsBank's database which contains a variety of over a thousand US newspapers respectively in addition to the 14 macroeconomic variables used by Neely et al. (2013) and also in the current study. JB is the empirical statistics of the Jarque-Bera test for normality. *** indicates rejection of normality at a 1% level of significance and ** at a 5% level. The Sharpe ratio is 0.10 and calculated as the mean of the log equity risk premium divided by its standard deviation.

Source: Authors' calculations.

4. Results and Interpretations

The main purpose of this study is to investigate the ability of government shutdown and debt ceiling to explain and predict the equity premium and compare it and other results for a different timeframe with those of Neely et al. (2013). As noted earlier, the out-of-sample predictive ability when compared to the historical average is an extremely important measure of any equity premium risk forecasting model where most predictors fail. The out-of-sample analysis results are in Table 3.

Column 2 shows that overall the majority of our predictors fail statistically in forecasting the equity premium by not reducing the MSFE with the exception of

some technical indicators with only VOL(1,12) and VOL(2,12) having economically significantly R_{OS}^2 statistics higher than 0.5% (Campbell and Thompson 2008). The better performance of technical indicators is in line with the findings of Neely et al. (2013) although all predictors seem to perform more poorly for our timeframe. When analysing this measure separately during expansions and recessions a clear trend emerges in that 15 predictors, of which the majority are technical indicators, have economically significant R_{OS}^2 statistics during recessions and none have during expansions. Of the principal component models the PC-ECON, PC-TECH and PC-ALL models do not contain any more information than the historical average overall based on the R_{OS}^2 statistic but the PC-TECH model does contain significantly more information during recessions. In other words, the technical indicators which are extracted as common factors from the principal component analysis have good predictive ability for equity risk premium. These common factors can be relied on for forecasting equity risk premium. Hence, they can act as signals to the equity market participants such as investors, businesses, households and policy makers.

The Clark and West (2007) MSFE-adjusted statistic reported in column 3 indicates that only Government Shutdown contains more information than the historical average (at a 10% level of significance) even though the R_{OS}^2 was negative. Intuitively, under the null hypothesis that the constant expected equity risk premium model generates the data, the predictive regression model produces a noisier forecast than the historical average benchmark, because it estimates slope parameters with zero population values. We thus expect the benchmark model MSFE to be smaller than the predictive regression model MSFE under the null. The MSFE-adjusted statistic accounts for the negative expected difference between the historical average MSFE and predictive regression MSFE under the null, so that it can reject the null even if the R_{OS}^2 statistic is negative.

This result is possible when comparing nested models as in this study. The MSFE decomposition results for the squared forecast bias and the remainder term are presented in columns 4 and 5 respectively and help us analyse bias efficiency trade-offs in the forecasts. The remainder term gives a sense of the forecast volatility as limiting the forecast volatility could help in reducing the remainder term (Rapach, Strauss, and Zhou 2010). The squared forecast bias and remainder term for the historical average are 0.03 and 20.73 respectively. 20 of our predictors, mostly technical indicators and one of our newly added variables, DEBTCEIL have squared biasedness lower than that of the historical average but only three technical indicators, namely MA(2,12), VOL(1,12) and VOL(2,12), have smaller remainder terms. Broadly these results are in line with the findings of Neely et al. (2013) in that the forecasts based on technical indicators are less biased and more efficient than those based on the historical average.

The 6th column shows the CER gains for an investor who has a relative risk coefficient of 5 and relies on the bivariate predictive regression forecasts given by (13), (14) or (15) instead of using the historical average forecast. The CER (in levels) is reported in addition to other portfolio performance measures including the Sharpe ratio in the 7th column and the average monthly turnover in the 8th column. The CER gains net of transaction costs, where the monthly transaction costs are calculated us-

ing the monthly turnover measures and proportional transaction costs are assumed to be 50 basis points per transaction (Pierluigi Balduzzi and Anthony W. Lynch 1999), are given in the 9th column.

The benchmark CER for the portfolio based on the historical average forecast is 2.11% for our time period. This is also positive for few other variables including the GOVSHUT variable with a value of 0.35%. In column 9, the CER gains after transaction costs have been accounted for are positive for 6 of our 16 economic variables (including the GOVSHUT with a value of 0.19%), 11 of our 14 technical indicators and the PC-TECH and PC-ALL models. When looking at the CER gains during expansions in column 11 there are only 3 economic variables (including GOVSHUT) and 2 technical indicators which show positive CER gains. Compared with the CER gains during recessions in column 13 where 11 of our economic variable (including GOVSHUT), 11 of our technical indicators and all of our principal component models show positive gains. This shows evidence of the benefits of using our predictors including the newly added GOVSHUT instead of the historical average to reduce risk in such periods. The Sharpe ratios tend to be higher or roughly the same as when using the historical average model with EP, the principal component model based on technical indicators and 9 separate technical indicators increasing the Sharpe ratio by 50% or more and only DP, DY, BM and the principal component model based on economic variables reducing it by 50% or more.

It is interesting to note that GOVSHUT has positive CER gains in both expansion and recession periods and a slightly higher Sharpe ratio compared to the historical average. Therefore, we provide evidence to show that news about government shutdown has predictive power for the equity market since it increases the uncertainty about employment and certain government expenditure. The resulting uncertainty can lead to reduced consumer confidence and hence demand as well as delays in investments by the business sector. All these could culminate in increased financial market stress, fall in stock prices, wider credit spreads and weak economic growth. Further, of our principal component forecasting models the one based on technical indicators performs the best overall with 2.57% CER gains after transaction costs and a Sharpe ratio of 0.15 and the one based on all the components performs the best during recessions with 29.20% CER gains and an overall Sharpe ratio of 0.10. The principal component forecasting model based on economic variables performs the worst overall with a 2.55% decrease after transaction costs and a Sharpe ratio of 0.04.

We used the recursive-squared residuals to show that there is some evidence of the errors being small during the peaks of debt-ceiling and government shutdown indices in 1995 and 2011. The recursive squared residuals from the predictive regression involving the equity risk premium and government shutdown, and equity risk premium and debt ceiling are presented in Figures 2 and 3, respectively.

Table 3 Monthly US Equity Risk Premium Out-of-Sample Forecasting Results

Predictor	Overall								Expansion		Recession	
	R_{Os}^2	MSFE-adjusted	$(\hat{\epsilon})^2$	Rem. terms	$\Delta(\text{ann \%})$	Sharpe ratio	Relative average turnover	$\Delta(\text{ann \%}, 50\text{bp cost})$	R_{Os}^2	$\Delta(\text{ann \%})$	R_{Os}^2	$\Delta(\text{ann \%})$
Historical average	-	-	0.03	20.7	2.11	0.10	2.99	1.91	-	-	-	-
DP	-4.09	-1.47	0.04	21.5	-4.47	0.00	2.29	-4.69	-6.06	-4.17	0.39	-7.35
DY	-3.65	-1.21	0.04	21.4	-3.80	0.02	2.90	-4.15	-5.90	-3.99	1.47	-3.69
EP	-1.98	0.45	0.04	21.1	5.51	0.21	1.54	5.44	-0.55	1.27	-5.23	31.86
DE	-2.14	-0.24	0.08	21.1	1.44	0.13	1.47	1.36	-0.89	-0.14	-4.98	11.43
RVOL	-0.07	0.02	0.04	20.7	-0.02	0.10	1.60	-0.12	0.11	0.31	-0.47	-1.90
BM	-2.31	-1.58	0.00	21.2	-3.17	0.02	2.28	-3.38	-3.83	-4.13	1.13	2.40
NTIS	-0.52	-0.24	0.01	20.8	1.64	0.12	1.91	1.47	-1.35	-1.28	1.36	19.79
TBL	-0.92	-0.39	0.00	20.9	1.30	0.11	1.71	1.17	-1.79	-1.23	1.05	17.10
LTY	-1.26	-0.59	0.04	20.9	0.13	0.10	1.76	0.00	-2.02	-1.92	0.47	13.06
LTR	-0.58	-1.67	0.03	20.8	-0.71	0.09	2.71	-1.01	-0.52	-0.35	-0.70	-2.87
TMS	-0.54	-0.58	0.04	20.8	0.09	0.10	1.46	0.01	-0.88	-0.56	0.21	4.34
DFY	-2.74	-0.11	0.00	21.3	-0.18	0.08	1.76	-0.32	-2.92	-2.92	-2.34	16.76
DFR	-1.94	0.09	0.03	21.1	1.48	0.12	13.05	-0.81	-1.02	-0.11	-4.03	11.22
INFL	-0.52	-0.16	0.03	20.8	-0.64	0.09	5.58	-1.47	-1.55	-1.26	1.82	2.64
DEBTCEIL	-1.30	1.09	0.00	21.0	-0.60	0.09	2.86	-0.92	-1.64	-0.59	-0.52	-0.70
GOVSHUT	-5.74	1.54*	0.07	21.8	0.35	0.11	1.89	0.19	-8.45	0.03	0.42	2.39
MA(1,9)	-2.19	-0.90	0.02	21.1	-1.76	0.06	2.69	-2.06	-2.41	-2.56	-1.69	3.02
MA(1,12)	-0.66	0.04	0.01	20.8	3.08	0.15	2.47	2.81	-2.37	-1.42	3.23	31.25
MA(2,9)	-0.75	-0.20	0.02	20.8	0.89	0.11	2.51	0.61	-1.35	-1.33	0.60	14.71
MA(2,12)	0.18	0.59	0.00	20.7	4.71	0.18	2.24	4.48	-1.94	-0.34	5.00	36.48
MA(3,9)	-1.90	-1.14	0.02	21.1	-1.65	0.07	2.54	-1.93	-1.42	-1.42	-2.99	-3.03
MA(3,12)	-1.59	-0.81	0.01	21.0	0.41	0.10	2.34	0.16	-2.14	-1.60	-0.36	12.83
MOM(9)	-0.32	0.32	0.00	20.8	4.04	0.17	2.39	3.77	-2.26	-0.39	4.08	31.83
MOM(12)	-0.48	0.15	0.01	20.8	3.47	0.16	2.34	3.20	-1.89	-0.55	2.72	28.69
VOL(1,9)	-0.06	0.31	0.01	20.7	3.03	0.15	4.04	2.45	-1.63	-0.84	3.52	27.31
VOL(1,12)	0.71	0.92	0.00	20.6	5.16	0.19	4.17	4.56	-1.10	0.18	4.83	36.51
VOL(2,9)	0.05	0.50	0.02	20.7	3.59	0.16	2.62	3.30	-1.21	-0.34	2.93	28.33
VOL(2,12)	0.59	0.89	0.01	20.6	4.66	0.18	2.51	4.37	-0.64	0.54	3.39	30.58
VOL(3,9)	-2.17	-0.36	0.05	21.1	-0.16	0.09	2.59	-0.45	-3.25	-2.03	0.29	11.49
VOL(3,12)	-0.11	0.67	0.01	20.7	4.23	0.17	2.51	3.94	-1.72	-0.06	3.55	31.18
PC-ECON	-6.36	-0.53	0.06	22.0	-2.26	0.04	2.51	-2.55	-4.74	-3.78	-10.02	6.86
PC-TECH	-0.73	0.13	0.01	20.9	2.90	0.15	2.84	2.57	-2.37	-1.03	3.01	27.59
PC-ALL	-5.51	-0.56	0.01	21.8	1.05	0.10	4.29	0.45	-4.93	-3.45	-6.85	29.20

Notes: This table summarises the empirical results from our forecasts of the equity risk premium in the United States. The equity risk premium is defined 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. The historical average forecast is simply using the mean of the equity risk premium to make a forecast. The popular economic variables are defined in table 1. DEBTCEIL and GOVSHUT refer to the number of mentions of “debt ceiling” and “government shutdown” in Access World News Bank’s database respectively. The technical indicators are defined in the methodology where MA’s refer to moving average rules, MOM’s refers to momentum rules and VOL’s refer to volume rules where r is the log equity risk premium (in percent). The principal component models are at the end in column 1. The second column reports the percentage reduction in mean squared forecast error (MSFE) when the forecast is compared to that of the historical average benchmark. Column 3 reports the Clark and West (2007) MSFE-adjusted statistic where *, **, *** indicates significance at a 10%, 5% and 1% level respectively. $(\hat{\epsilon})^2$ and Rem. Terms are the squared forecast bias and remainder terms respectively and reported in columns 4 and 5. Column 6 reports the annualized certainty equivalent return (CER) gain, Δ , for an investor who uses the specified regression forecast instead of the historical average benchmark forecast. Sharp ratio is the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. Relative average monthly turnover is the percentage of wealth traded each month. For the portfolio based on the historical average forecast, the table gives the average monthly turnover. For all other portfolios it gives the average monthly turnover relative to that of the turnover based on the historical average. The ninth column reports Δ whilst taking into account transaction costs of 50 basis points per transaction. The percentage reduction in mean squared forecast error and Δ are reported for NBER dated expansions and recessions in the last 4 columns.

Source: Authors’ estimations.

5. Conclusions

This study investigates the predictability of the equity risk premium in the United States, which is defined as the return on the S&P 500 total return index in excess of the interest rate on the three month Treasury bill, and the gains a risk averse investor could receive for using the predictive regression model forecast over the historical average forecast. This is done for a monthly out-of-sample period of 1995:01 to 2012:12 using an in-sample period of 1985:11-1994:12. We use a comprehensive set of 16 economic and 14 technical predictors, accounted for expansions and recessions and made use of a standard predictive regression framework and principal component models and evaluate the out-of-sample predictive ability. In addition to the widely used predictors in the literature (see Neely et al. 2013) our study includes two previously unused economic variables related to economic policy uncertainty in the United States namely government shutdown and debt ceiling. These are measured as the percentage of total news articles in which they are mentioned and can be seen as the public’s perception of how likely they are to occur or affect financial markets. Of the newly added variables only government shutdown plays a significant statistical and economical role by outperforming the historical average benchmark in predicting the US equity risk premium. Possible policy implications and uses for these results include that portfolio managers could use news of the government shutdown as a predictor of the equity premium in their allocation decisions and possibly provide economic value for their clients. Interestingly all but 5 (including the debt ceiling) of our predictors and all of the principal component models show CER gains during recessions which is indicative of their value in predicting the equity risk premium during riskier times when stock returns tend to be more volatile hence more risky and have spillovers to the real economy as found by Nikolaos Giannellis, Angelos Kanas, and Athanasios P. Papadopoulos (2010). The general findings for the other variables are in line with the finding by Neely et al. (2013), in that the technical indicators tend to perform better when compared to economic indicators and most predictors tend to predict the equity premium better during recessionary periods. However the forecast-

ing power is slightly weaker for our more recent timeframe and the complementary behaviour of economic variables and technical indicators is not visible. In light of the statistical performance of our models, future research on this topic should concentrate on forecasting using a larger selection of statistical models as used in Gupta et al. (2013).

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