INCORPORATING ECONOMIC POLICY UNCERTAINTY IN US EQUITY PREMIUM MODELS: A NONLINEAR PREDICTABILITY ANALYSIS

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ABSTRACT

Information on economic policy uncertainty does matter in predicting the US equity premium, especially when accounting for structural instabilities and omitted nonlinearities in their relationship, via a quantile predictive regression approach over the monthly period 1900:1-2014:2. Unlike as suggested by a linear mean-based predictive model, the extended quantile regression model with the incorporation of the EPU proxy, enhances significantly the out-of-sample stock return predictability. This is observed especially when the market is neutral, exhibits a side or mildly upward trending behavior, yet not when the market appears to turn highly bullish.

JEL Codes: C22; C53; E60; G10

Keywords: stock markets; economic uncertainty; predictability; quantile regression

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1. INTRODUCTION

The existing literature on forecasting US stock returns is vast. For practitioners it is of utmost importance to use real-time forecasts in optimal asset allocation, whilst for academics return predictability challenges market efficiency which in turn leads to more realistic asset pricing models (Rapach and Zhou, 2013). However, stock market forecasting is highly controversial as it inherently incorporates stochastic as well as nonlinear components. Understandably a wide array of models e.g., univariate and multivariate, linear and nonlinear ones including various types of predictors namely domestic and international financial, macroeconomic, institutional and behavioural indices, have been recently utilized (Aye *et al.,* 2015). Not surprisingly, the empirical evidence is mixed.

Asset returns are functions of the state variables of the real economy, and the real economy itself displays significant fluctuations. Beyond the standard theoretical justifications of such fluctuations which are mostly based on productivity and/or policy shocks, a recent strand of literature as in Bloom (2009) and Jones and Olson (2013) relates the impact of various forms of policy-generated uncertainty to movements in macroeconomic and financial variables which are expected to affect stock returns. Primarily in-sample empirical evidence in this regard can be found in Antonakakis *et al.,* (2013), Kang and Ratti (2013), Gupta *et al.,*(2014), Bekiros *et al.,* (2015), Chang *et al.,* (2015) and Jurado *et al.,* (2015).[1]

Against this backdrop, and under the widely held view that predictive models require out-of-sample validation (Rapach and Zhou, 2013), the objective of this paper is to investigate whether the news-based measure of economic policy uncertainty (EPU) introduced by Baker *et al.* (2013) could help in forecasting the S&P500-based equity

[1]Amongst the papers cited, Gupta *et al.,* (2014) is the only one to analyse out-of-sample forecasting of the US equity premium based on EPU using a linear predictive regression model, but it failed to beat the random-walk model.

premium. We concentrate on a very broad monthly out-of-sample period (1909:8-2014:2) which encompasses all stock market events in the US over the 20th and the 21st century. Based on the recent contribution by Bekiros and Gupta (2015) who proved the relationship between returns and predictors not being linear, we consider a quantile predictive regression model over and above the standard linear modelling. The quantile-based approach is clearly more informative relative to any linear model, as it investigates the ability of the EPU to forecast the entire conditional distribution of the equity premium, rather than being restricted just to the conditional-mean.

To the best of our knowledge, this is the first attempt to analyse the forecastability of the EPU vis-à-vis the US equity premium, utilizing a quantile regression approach. The rest of the paper is organized as follows: section 2 presents the econometric methodology while section 3 describes the data and discusses the results. Section 4 concludes.

2. QUANTILE PREDICTIVE REGRESSION MODEL

The classical mean regression model is given by:

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

where r_{t+1} is the observed excess return at time $t+1$, $x_{i,t}$ is a specific regressor / predictor at time t, which in our work is EPU and ε_{t+1} is the error term assumed to be independent with zero mean and variance σ^2. The ordinary least squares (OLS) estimators $\hat{\alpha}_i, \hat{\beta}_i$ of the parameters in the predictive mean regression model can be estimated by minimizing the quadratic expected loss, $\sum_{t=0}^{T-1}(r_{t+1} - \alpha_i - \beta_i x_{i,t})^2$ with respect to α_i, β_i. Then, the point forecast of the equity premium at time $t+1$, can be obtained as: $\hat{r}_{i,t+1} = \hat{\alpha}_i + \hat{\beta}_i x_{i,t}$.

The aforementioned model specification is primarily devised to predict the mean of r_{t+1}, and not its entire distribution. Koenker and Bassett (1978) showed that Quantile Regression estimators are more efficient and robust than mean regression estimators in cases where nonlinearities and deviations from normality exist. Hence, we consider the quantile regression model of the following form:

$$r_{t+1} = \alpha_i{}^{(\tau)} + \beta_i{}^{(\tau)} x_{i,t} + \varepsilon_{t+1} \qquad i = 1, \ldots, N, \qquad (2)$$

where $\tau \in (0,1)$ and ε_{t+1} are assumed independent derived from an error distribution $g_\tau(\varepsilon)$ with the τ-th quantile equal to 0. Model (2) suggests the τ-th quantile of r_{t+1} given $x_{i,t}$, is $Q_\tau(r_{t+1}|x_{i,t}) = \alpha_i{}^{(\tau)} + \beta_i{}^{(\tau)} x_{i,t}$, where the intercept and the regression coefficients depend upon τ. The estimators of the parameters of the linear quantile regression model in Eq. (2), $\alpha_i{}^{(\tau)}, \beta_i{}^{(\tau)}$, can be obtained by minimizing the sum $\sum_{t=0}^{T-1} \rho_\tau(r_{t+1} - \alpha_i{}^{(\tau)} - \beta_i{}^{(\tau)} x_{i,t})$, where $\rho_\tau(u) = u(\tau - I(u < 0)) = \frac{1}{2}[|u| + (2\tau - 1)u]$. The forecast of the τ-th quantile of the distribution of the equity premium at time $t + 1$ is obtained as $\hat{r}_{i,t+1}(\tau) = \alpha_i{}^{(\tau)} + \beta_i{}^{(\tau)} x_{i,t}$.

3. EMPIRICAL RESULTS

The dataset used in the present study covers the monthly period 1900:1-2014:2 and incorporates two variables, namely the US equity premium and the news-based measure of economic policy uncertainty (EPU) introduced by Baker *et al.* (2013). The equity premium is calculated as the difference of the continuously compounded S&P 500 returns, including

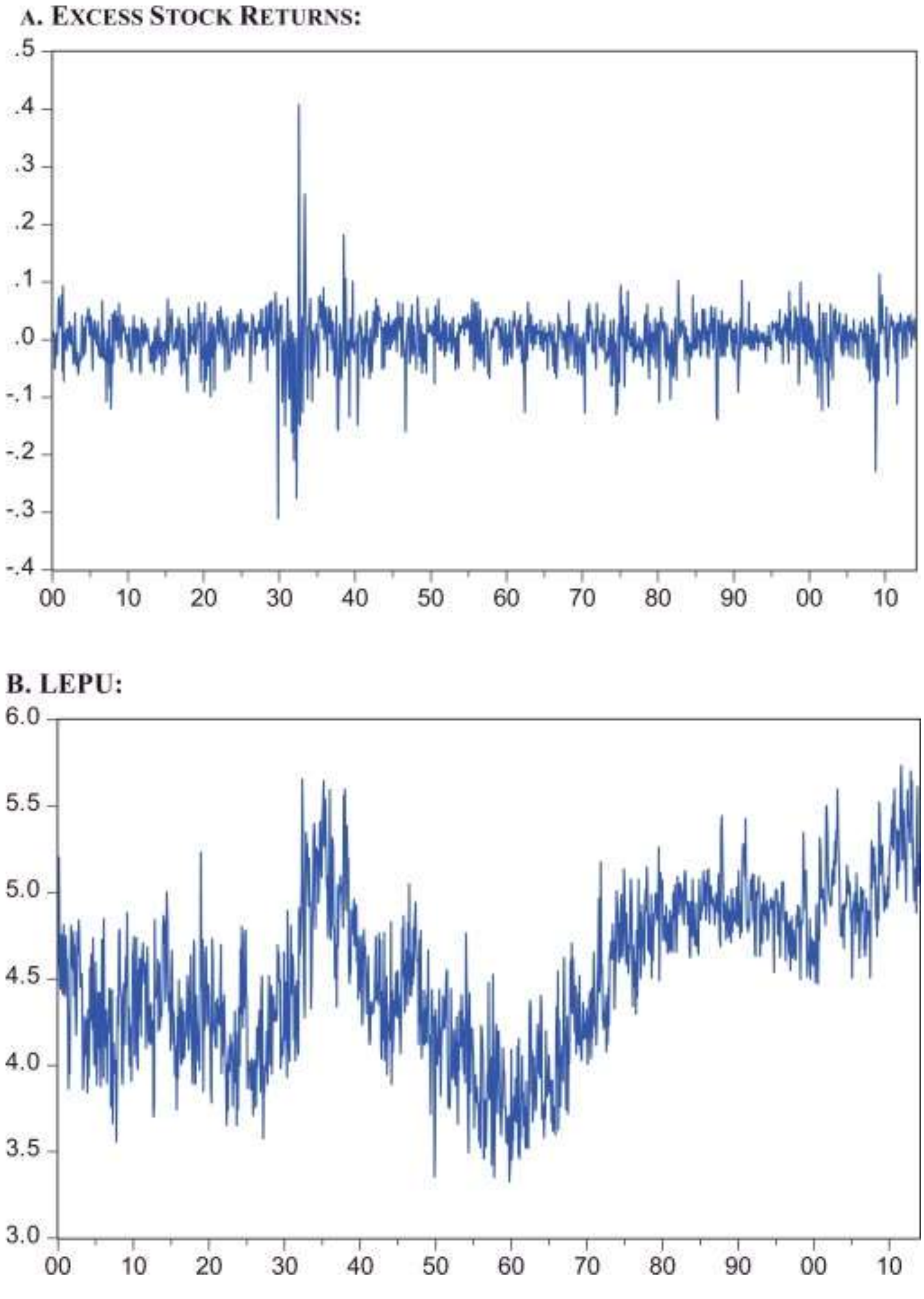

Fig. 1. Data plots of excess returns and natural Logarithm of Economic Policy Uncertainty (LEPU).

dividends and the three-month Treasury bill rate.[2] The EPU index is log-transformed[3] and it is constructed based on month-by-month searches of newspaper articles related to economic and policy uncertainty.[4] The start and end date of the sample is purely driven by the data availability of the EPU. Fig. 1 plots the equity premium and the natural logarithms of the EPU index.

To determine our in-sample and out-of-sample segmentation with the models in Eq. (1) and Eq. (2) being estimated recursively over the latter, we conduct the Bai and Perron (2003) tests of multiple structural breaks on equation Eq. (1). The test reveals five breaks specifically at 1909:8, 1921:9, 1929:10, 1940:7 and 1966:2, hence our in-sample includes 1900:1-1909:7, while the rest is being utilized as the out-of-sample.[5] Firstly, when we apply the Jarque-Bera test on the residuals recovered from Eq. (1) the null of normality is overwhelmingly rejected at the highest levels of significance. Furthermore, the Brock *et al.,* (1996, BDS) test when applied on these residuals it also rejects the null of serial dependence at all possible dimensions at all levels of significance, thus provides strong evidence of nonlinearity between the US equity premium and EPU. The results from the structural instability analysis as well as the nonlinearity testing, highlight on the one hand the inappropriateness of the linear predictive regression specification defined in Eq.(1), while on the other hand indicate the necessity to employ a quantile predictive regression, as in Eq. (2).[6]

For the sake of completeness and comparability, we present in Table 1 the forecasting results by the linear predictive regression, aside from the quantile predictive regressions over $\tau = 0.05, 0.10, 0.15 \ldots 0.95$. The entries in the table report the ratio of the mean square

[2] The equity premium until 2013:12, is calculated based on the data available on the website http://www.hec.unil.ch/agoyal/. Beyond this period, data from the FRED database of the Federal Reserve Bank of St. Louis are used.
[3] Standard unit root tests reveal that the natural logarithm of the EPU is stationary. The details of these tests are available upon request from the authors.
[4] Data and further details are available at: http://www.policyuncertainty.com/us_historical.html.
[5] Complete details of the structural break tests are available upon request from the authors.
[6] Complete details of the Jarque-Bera and BDS tests are available upon request by the authors.

forecast errors of Eq. (1) relative the historical average $\hat{r}_{i,t+1} = \hat{\alpha}_i$ and the same for Eq. (2) relative to the prevailing quantile model $\hat{r}_{i,t+1}(\tau) = \alpha_i^{(\tau)}$. If the ratio score is less than one, then the model with the predictor incorporated outperforms the model without it. It is also important to test whether the superior performance of the model with the EPU - if it holds - is statistically different from the appropriate benchmark. Given that one model nests its corresponding benchmark, we use the *MSE-F* test statistic by McCracken (2007) in order to check whether the outperforming evidence of the ratio being less than one versus the model with uncertainty is statistically significantly.

As it is observed from Table 1 for the linear predictive regression, EPU fails to beat the forecasting performance of the benchmark model. This result was similarly reported by Gupta *et al.* (2014). However, given the evidence non-normality and nonlinearity, the results of the benchmark linear model cannot be robustly relied upon, hence we move on to the quantile predictive regression model. As we observe from Table 1, the quantile regression model with the included EPU index outperforms the prevailing quantile benchmark significantly at one percent level for $\tau \in [0.05, 0.50]$, i.e., around the lower-end to the median of the distribution of the equity premium.[7] Interestingly though, EPU fails to provide significant forecastability beyond the median.

Overall, unlike as suggested by the linear (mean-based) predictive regression model, the quantile regression model demonstrates that the EPU enhances significantly the out-of-sample predictability especially when the stock market is performing poorly to moderate, yet not when the market appears to turn highly bullish.

[7] Qualitatively similar results were obtained when we applied Bayesian versions of the quantile and nonparametric quantile regressions. Complete details are available upon request by the authors.

TABLE 1: MSFE FOR LINEAR AND QUANTILE PREDICTIVE REGRESSION MODELS

Quantile Regression (τ)	$MSFE_m$ / $MSFE_b$
0.05	0.8964***
0.10	0.8646***
0.15	0.8422***
0.20	0.8858***
0.25	0.8761***
0.30	0.9186***
0.35	0.9245***
0.40	0.9487***
0.45	0.9703***
0.50	0.9891***
0.55	1.0182
0.60	1.0561
0.65	1.0652
0.70	1.1097
0.75	1.1049
0.80	1.1470
0.85	1.1666
0.90	1.2385
0.95	1.2852
Linear Regression	1.0030

Note: *** indicates the 1% level of significance for the *MSE-F* statistic, whilst τ specifies the quantile; $MSFE_m$ / $MSFE_b$ signifies the MSFE ratio of the corresponding model over the one generated by the benchmark

4. CONCLUSIONS

The importance of precise stock return forecasts both for practitioners and academics is well-recognized and strongly pursued by market agents. Recent works in the literature provide some conflicting in-sample evidence in favor of the assumption that the economic policy uncertainty index (EPU) possibly drives stock returns.

In an attempt to further substantiate or not this evidence, we compare the forecastability of the US equity premium vis-à-vis the EPU using linear and quantile predictive regression models. The linear regression model with EPU fails to outperform the benchmark model of the historical average of equity premium. However, after suitable testing and thereby accounting for the presence of non-normality and nonlinearity, linear modeling results in misspecification. When we use a quantile predictive regression model, we observe that the economic policy uncertainty index contains significant out-of-sample information around the lower-end to the median of the distribution of the equity premium, albeit not when the market behavior is clearly bullish.

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Appendix A

Table A1. Summary statistics.

	Excess stock returns	EPU	Residual Eq. (1)
Mean	0.0012	4.5266	0.0000
Median	0.0048	4.5506	0.0038
Maximum	0.4073	5.7349	0.4052
Minimum	−0.3104	3.3271	−0.3100
Std. Dev.	0.0431	0.4681	0.0431
Skewness	−0.4217	−0.0829	−0.4463
Kurtosis	14.3285	2.3859	14.2688
Jarque-Bera	7366.4150	23.0979	7288.9470
p-value	0.0000	0.0000	0.0000
Obs.	1370	1370	1369

Note: EPU denotes economic policy uncertainty in natural logarithms; Eq. (1): $r_{t+1}=\alpha_i+\beta_i x_{i,t}+\varepsilon_{t+1}$rt+1=αi+βixi,t+εt+1 Std. Dev. symbolizes the Standard Deviation; *p*-value corresponds to the test of normality based on the Jarque–Bera test.

Table A2. BDS test.

m	***z*-statistic of residual benchmark model**	***p*-value**	***z*-statistic of residual Eq. (1)**	***p*-value**
2	8.7461	0.0000	8.6362	0.0000
3	9.4873	0.0000	9.3875	0.0000
4	10.3894	0.0000	10.2740	0.0000
5	10.9483	0.0000	10.9300	0.0000
6	11.7988	0.0000	11.7752	0.0000

Note: m stands for the embedded dimension; benchmark model: $r_{t+1}=\alpha_i+\varepsilon_{t+1}$rt+1=αi+εt+1; Eq. (1): $r_{t+1}=\alpha_i+\beta_i x_{i,t}+\varepsilon_{t+1}$rt+1=αi+βixi,t+εt+1; *p*-value corresponds to the test of *i.i.d.* residuals based on the *z*-statistic of the BDS test.

Table A3. Bai and Perron (2003) test of multiple structural breaks.

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value	
1	2.7757	5.5514	5.5514	11.02	
2	3.1542	6.3083	6.6334	10.48	
3 *	6.1346	12.2691	14.0693	9.61	
4 *	6.2940	12.5881	15.4305	8.99	
5 *	6.0751	12.1502	15.7524	8.50	
UDMax statistic*		12.5881	UDMax critical value**		11.69
WDMax statistic*		15.7524	WDMax critical value**		12.33
Sequential F-stat. determined breaks:		0			
Significant F-stat. largest breaks:		5			
UDmax determined breaks:		4			
WDmax determined breaks:		5			

Estimated break dates:

1: 1942:05

2: 1929:10, 1940:07

3: 1921:09, 1929:10, 1940:07

4: 1909:08, 1921:09, 1929:10, 1940:07

5: 1909:08, 1921:09, 1929:10, 1940:07, 1966:02

Note: The Bai–Perron tests is presented for 1 to *M* globally determined breaks. The sample spans 1900M01– 2014M02. The investigated EPU breakpoint model includes the first lag of EPU (i.e., EPU(−1)) and a constant term C. We allow for heterogeneous error distributions across breaks; * denotes significance at the 0.10 level, while ** denotes the Bai–Perron critical values (*Econometric Journal*, 2003).