The Role of Partisan Conflict in Forecasting the U.S. Equity Premium: A Nonparametric Approach♦

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Highlights

• We employ a nonparametric predictive regression approach.

• The sample period is monthly over 1981:1–2016:6.

• Our nonparametric coefficient regression includes a partisan conflict index.

• The partisan conflict matters in forecasting the out of sample U.S. equity premium.

Abstract

Information on partisan conflict is shown to matter in forecasting the U.S. equity premium, especially when accounting for omitted nonlinearities in their relationship, via a nonparametric predictive regression approach over the monthly period 1981:01-2016:06. Unlike as suggested by a linear predictive model, the nonparametric functional coefficient regression that includes the partisan conflict index enhances significantly the out-of-sample excess stock returns predictability. This result is found to be robust when we use a quantile predictive regression framework to capture nonlinearity, especially when the market is found to be in its bullish mode (i.e., upper quantiles of the conditional distribution of the equity premium).

JEL Codes: C14, C22, C53, G1, G18
Keywords: Equity Premium, Partisan Conflict Index, Linear and Nonparametric Predictive Regressions

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1. Introduction

The existing literature on forecasting stock returns and/or equity premium of the U.S. economy is vast to say the least (Rapach and Zhou, 2013). On one hand, practitioners in finance require real-time forecasts of stock returns for asset allocation. On the other hand, academics in finance are interested in stock return forecasts, since they have important implications for tests of market efficiency, which in turn, helps to produce more realistic asset pricing models. However, stock return forecasting is highly challenging, since it inherently contains a sizable unpredictable component. Understandably, a wide array of models (univariate and multivariate; linear and nonlinear), and predictors (behavioural, financial, institutional and macroeconomic) have been used, with mixed results depending on predictors, models and sample periods (Rapach and Zhou, 2013).

In this regard, Cheng et al., (2016), using a structural Bayesian vector autoregressive model, provide some evidence of the ability of U.S. partisan conflict in affecting stock returns, besides other macroeconomic variables, of not only the U.S. economy, but also the Euro area. Note that, Cheng et al., (2016) used the Partisan Conflict Index (PCI) developed by Azzimonti (2015), which in turn, is based on the frequency of newspaper coverage of articles reporting political disagreement about government policy, both within and between national parties in the U.S.

The ability of the PCI to affect stock returns can be explained intuitively as follows: Recently, Azzimonti (2015) has developed a reduced-form political economy model with Bayesian learning. In this model, investment returns depend on the state of the economy, with these returns taking extremely low values during low probability events, such as a financial crisis, a sovereign debt crisis, or a war. In this framework, policymakers can reduce the probability of rare events by adopting preventive policies or undertaking reforms, but face political costs. When parties are polarized and the government is divided, partisan conflict is elevated, and the quality of policies adopted is lower. In the process, partisan conflict exacerbates economic risk by increasing the likelihood of rare events. As discussed in detail in Manela and Moreira (forthcoming), recent theoretical frameworks have emphasized time variation in rare event risk as a source of aggregate asset price fluctuations, which in turn, implies a link between partisan conflict and the equity market. In addition, as shown by Cheng et al., (2016) PCI leads to business cycle fluctuations, and given that, asset returns are functions of the state variables of the real economy, fluctuations in it due to partisan conflict is likely to affect the stock market via movements in real activity (Bekiros et al., 2016).

Against this backdrop, and under the widely held view that predictive models require out-of-sample validation (Campbell, 2008), the objective of this paper is to investigate whether PCI could help in forecasting the S&P500-based equity premium. We concentrate on a monthly out-of-sample period (1998:10-2016:06), given an in-sample period of 1981:01 to 1998:09. In the process, we test whether the in-sample evidence that PCI causes U.S. stock returns as shown by Cheng et al., (2016), holds for a forecasting exercise.

Traditionally, studies dealing with stock returns and equity premium prediction have used a linear predictive regression framework. However, recent contributions to the literature have pointed out that the relationship between returns and predictors is not linear (Bekiros et al., 2016). Given this, the literature has resorted to Markov-switching, smooth transition threshold, neural networks, non- or semi-parametric, time-varying coefficient and quantile models (Rapach and Zhou, 2013). In this paper, we address the issue of non-linearity between excess returns and the predictive variable (i.e., the PCI), which we show to exist based on formal tests of nonlinearity, by considering a nonparametric approach. Specifically speaking, we consider the functional coefficient predictive regression model of Cai et al., (2000), where the coefficients are not specified within a fixed parametric functional form, but their structure is estimated from the data with a local linear smoother. The advantage of this nonparametric model is that it is less prone than other more general non-parametric formulations to the so called *curse of dimensionality*, since the functional coefficients are one-dimensional, and therefore ensures the feasibility of the estimation problem (Bruno, 2014).

To the best of our knowledge, this is the first attempt to analyse the forecastability of the PCI vis-à-vis the U.S. equity premium, utilizing a nonparametric regression approach. Note the results are compared with a linear autoregressive model, as well as a linear predictive regression model which includes the lagged PCI. 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. Methodology

As discussed above, this paper uses the functional coefficient regression (FCR) method to forecast the U.S. equity premium using the PCI as a predictor. The method allows for flexibility in the structure of fitted regression model without suffering from the overparameterization problem associated with nonparametric models. The general form of a FCR model can be expressed as follows:

$$y_t = a_0(u_t) + \sum_{j=1}^{p} a_j(\boldsymbol{u_t}) x_{jt} + \varepsilon_t \tag{1}$$

where y_t is the dependent variable at time t, $a_j(\cdot)$'s are the functional coefficient functions to be estimated, and $\boldsymbol{x} = (x_{1t}, \dots, x_{pt})$ a vector of predictor variables that might include lags of $y_t$and x_{jt}. u_t is the state variable that describes the nonlinear dynamics in the excess returns.

The FCR model used in this paper is as follows:

$$y_t = a_0(u_t) + a_1(u_t) y_{t-1} + a_2(u_t) x_{1t-1} + \varepsilon_t \tag{2}$$

where x_{1t} is the natural log of the PCI at time t, y_t is the excess returns of the U.S. at time t, $u_t = (x_{1t-1})$ is the state variable at time t that captures the nonlinear dynamics of the PCI at time $t-1$, and $\mathcal{E}_t$ is the error term assumed to be *i.i.d*. The choice of one lag is based on the Schwarz information criterion (SIC). Note that, assuming that a_0, a_1, and a_2 are fixed coefficients, gives us the standard predictive regression model, while setting a_2=0, provides us with our benchmark of AR(1) model.

The functional coefficients $a_0(.)$, $a_1(.)$, and $a_2(.)$ are estimated by making use of a non-parametric technique known as the local linear estimation. For the purpose of convergence in estimation, it is assumed that these functional coefficients $a_j(\cdot)$ are continuous and have a finite second derivative. The optimal bandwidth required for the nonparametric estimation is obtained by using the cross-validation method as in Cai et al. (2000).

3. Data and Results

The dataset used in the present study covers the monthly period 1981:1-2016:6, and incorporates two variables, namely the U.S. equity premium and the news-based index of partisan conflict (PCI) introduced by Azzimonti (2015). The equity premium is calculated as the difference of the continuously compounded S&P 500 returns and the three-month Treasury bill rate.[1] The PCI index is log-transformed[2], and tracks the degree of political disagreement among U.S. politicians at the federal level by measuring the frequency of newspaper articles in major U.S. newspapers (Washington Post, New York Times, Los Angeles Times, Chicago Tribune, and Wall Street Journal) reporting disagreement in a given

[1]The S&P500 nominal stock price data is obtained from the data segment of the website of Professor Robert J. Shiller (http://www.econ.yale.edu/~shiller/data.htm), while the three-month Treasury bill rate data is derived from the FRED database of the Federal Reserve Bank of St. Louis.

[2] Standard unit root tests reveal that the natural logarithm of the PCI is stationary. The details of these tests are available upon request from the authors.

month.[3] The start and end date of the sample is purely driven by the data availability of the PCI. Figure A1 plots the equity premium and the natural logarithms of the PCI index, while Table A1 reports the summary statistics of these two variables in the Appendix of the paper.

To determine our in-sample and out-of-sample segmentation, we conducted the Bai and Perron (2003) tests of multiple structural breaks on the fixed coefficient version of equation (2). However, we failed to detect any breaks.[4] Given this, we followed Rapach et al., (2005) in splitting the in-sample and out-of-sample in a way such that both of them have equal numbers of observations. This in turn implied that the in-sample period covered 1981:01-1998:09, while the out-of-sample is 1998:10-2016:06, i.e., 213 observation each. Then when we apply the Brock *et al.*, (1996, BDS) test on the residuals of equation (2) (estimated via OLS), the test, as reported in Table A2 in the Appenidx, rejects the null of *i.i.d.* at all possible dimensions at least at the five perecent level of significance, thus providing strong evidence of nonlinearity between the US equity premium and PCI. This result suggests the inappropriateness of the linear predictive regression specification that would be obtained by setting the coefficients of equation (2) as constants.

For the sake of completeness and comparability, we present in Table 1 the forecasting results from the linear predictive regression, aside from the FCR model. The entries in the table report the ratio of the mean square forecast errors (MSFEs) of these two models relative to the benchmark AR(1) model, based on a recursive estimation over the out-of-sample period. If the ratio 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 PCI - if it holds - is statistically different from the appropriate benchmark. Given that both the models nest the benchmark, we use the *MSE-F*

[3] Data and further details are available at: https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index.
[4] Complete details of the various structural break tests are available upon request from the authors.

test statistic of McCracken (2007) in order to check whether in the case(s) where the ratio of MSFEs is(are) less than one, significantly outperforms the AR(1).

Table 1. Relative (to Benchmark AR(1)) Mean Square Forecast Errors (MSFEs) of Linear and Nonparametric Predictive Regression Models

AR(1): $MSFE_b$	Linear Model: $MSFE_m/MSFE_b$	Nonparametric Model: $MSFE_m/MSFE_b$
0.1592	1.5301	0.9415 [13.2293*]

Note: $MSFE_m$ / $MSFE_b$ signifies the Mean Square Forecast Error (MSFE) ratio of the corresponding linear or nonparametric (FCR) regression models with respect to the one generated by the AR(1) benchmark model; Entry in square bracket is the *MSE-F* test statistic $[=MSFE_b/MSFE_m - 1] \times (T - R - h + 1)$, where where T is the total sample, R is the number of observations used in estimation of the model from which the first forecast is derived (i.e. the in-sample portion of the total number of observations), and h is the forecast horizon; * indicates the 1% level of significance of the *MSE-F* statistic of McCracken (2007), with the critical values being: 3.5840, 1.5480, 0.7980 at 1 percent, 5 percent and 10 percent respectively.

As it is observed from Table 1, the linear predictive regression that includes the PCI, fails to beat the forecasting performance of the AR(1). However, given the evidence of nonlinearity, the results from the linear model cannot be relied upon, hence we move on to the FCR model. As we observe from Table 1, the FCR model outperforms the benchmark significantly at one percent level of significance. Hence, unlike the linear predictive regression model, the nonparametric regression model demonstrates that the PCI enhances significantly the out-of-sample predictability of the U.S. equity premium, highlighting the need to model nonlinearity present in the relationship between the equity premium and the PCI.[5,6]

5 Since Cheng et al., (2016) showed that the PCI also affected the Euro Stoxx 50, we also conducted an out-of-sample forecasting exercise for the excess returns of the Euro area. However, both the linear and the nonparametric models failed to beat the AR(1). Complete details of these results are available upon request from the authors.

6 Based on the suggestions of an anonymous referee, we conducted various robustness checks. First, we used the interest rate on the year government bond as a measure of the risk-free rate; second, we used the economic policy uncertainty index as used in Bekiros et al., (2016), instead of the PCI; and third, we carried out a forecasting analysis based on the Vector Autoregressive (VAR) used by Cheng et al., (2016). We found that, i.e., irrespective of the measure of the risk-free rate, excess return is only predictable by PCI based on the FCAR model. When the PCI is replaced by the EPU, the superiority of the FCAR model continues to hold. Finally, the

Based on the suggestion of an anonymous referee, we also estimated the quantile predictive regression as in Bekiros et al., (2016), which in turn, provide an alternative approach to capture the nonlinear relationship between excess returns and the PCI. The results have been reported in Table 2. As can be seen, barring the quantile 0.10, the quantile predictive regression model including the PCI outperforms the model without it over the quantile range of 0.20 to 0.90. Based on the *MSE-F* test, the gains are significant at least at the 5 percent level of significance for the quantiles of 0.30 to 0.90. The results suggest, that barring when the market is at an extreme bear phase, political discord provides important information in forecasting the market relatively more strongly when it is in its bullish stage. The superior performance of the quantile regression model, as with the FCR framework, again highlights the importance of modeling nonlinearity when forecasting stock returns.

Table 2. Relative Mean Square Forecast Errors of Quantile Predictive Regression Model

Quantile Regression (τ)	$MSFE_m$ / $MSFE_b$
0.1	1.0028 [-0.5880]
0.2	0.9986 [0.2974]
0.3	0.9802 [4.3083*]
0.4	0.9869 [2.8332$^\#$]
0.5	0.9906 [2.0310$^\#$]
0.6	0.9914 [1.8545$^\#$]
0.7	0.9820 [3.9064*]
0.8	0.9849 [3.2626$^\#$]
0.9	0.9748 [5.5027*]

Note: $MSFE_m$ / $MSFE_b$ signifies the Mean Square Forecast Error (MSFE) ratio of the quantile regression model over the one generated by the benchmark; * and $^\#$ indicates the 1 percent and 5 percent levels of significance for the *MSE-F* statistic of McCracken (2007) reported in square brackets (with the critical values being: 3.5840, 1.5480, 0.7980 at 1 percent, 5 percent and 10 percent respectively), whilst τ specifies the quantile.

VAR model with the PCI is outperformed by the model without it. These robustness checks, details of which are available upon request from the authors, continue to validate our main conclusion: PCI (or EPU) tends to forecast excess returns, but only when we allow for nonlinearity in the model structure, given the misspecification associate with the linear models, whether it is a predictive regression or a VAR model.

4. Conclusions

The importance of precise stock return forecasts both for practitioners and academics is well-recognized. Recent works in the literature provide some in-sample evidence that partisan conflict possibly drives stock returns.

In an attempt to further substantiate this evidence, we compare the forecastability of the US equity premium vis-à-vis the partisan conflict index (PCI) using linear and nonparametric predictive regression models. The linear regression model with PCI fails to outperform the benchmark AR(1) model of equity premium. However, tests of nonlinearity show that the linear model is misspecified. Given this, when we use a nonparametric approach, we observe that the PCI contains significant out-of-sample information for the U.S. equity premium. Our results are also robust to an alternative approach of modelling nonlinearity via the quantile predictive regression model, with this framework showing stronger forecasting gains at the upper end of the conditional distribution of the excess stock returns, i.e., when the market is in its bullish mode.

Partisan conflict has been shown to also affect equity market volatility (Bechtel and Füss, 2008). Hence, it might be worthwhile to forecast (realized) volatility using partisan conflict, as part of future research.

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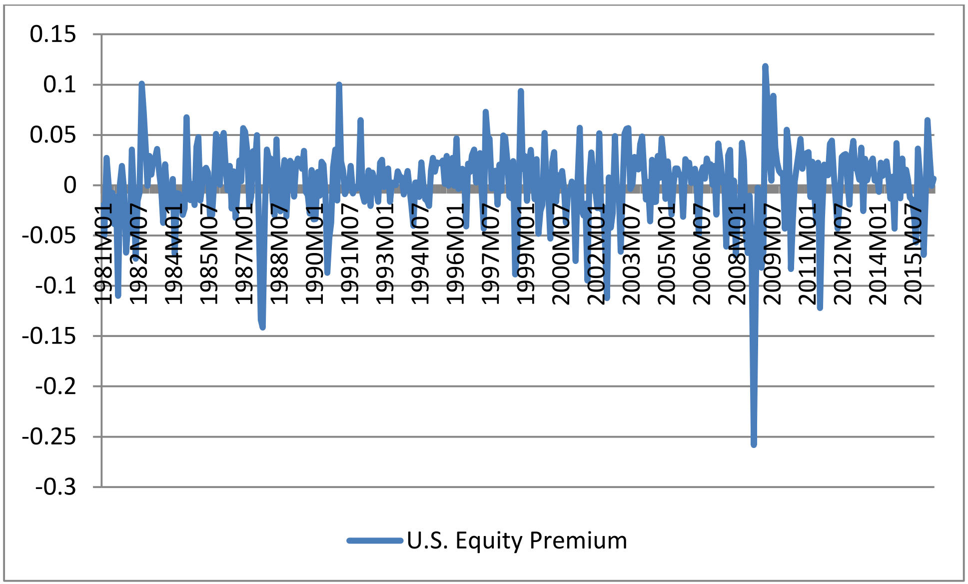
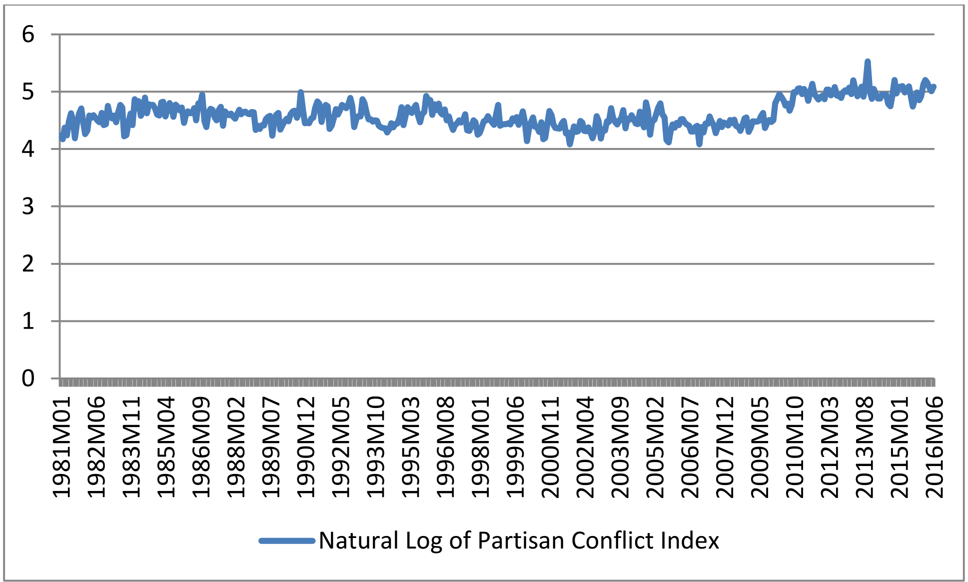
Appendix:

Figure A1. Data Plots





Note: Equity premium is calculated as the log stock S&P500 returns in excess of a risk-free rate (three-month Treasury bill rate), while the partisan conflict index is the degree of political disagreement among U.S. politicians at the federal level by measuring the frequency of newspaper articles in major U.S. newspapers.

Table A1. Summary Statistics

	U.S. Equity Premium	Natural Log of Partisan Conflict Index
Mean	0.0019	4.6029
Median	0.0050	4.5599
Maximum	0.1185	5.5298
Minimum	-0.2583	4.0807
Std. Dev.	0.0368	0.2373
Skewness	-1.3402	0.5598
Kurtosis	9.8370	2.9650
Jarque-Bera	957.2374	22.2679
p-value	0.0000	0.0000
Observations	426	426

Note: Std. Dev. symbolizes the Standard Deviation; *p*-value corresponds to the null of normality based on the Jarque-Bera test.

Table A2. BDS Test

m	*z*-statistic of Residuals of Equation (2) with Fixed Coefficients	*p*-value
2	2.3657	0.0180
3	3.0489	0.0023
4	3.4649	0.0005
5	3.4678	0.0005
6	3.7982	0.0001

Note: *m* stands for the number of (embedded) dimension which embed the time series into m-dimensional vectors, by taking each *m* successive points in the series; *p*-value corresponds to the null of *i.i.d.* residuals based on the *z*-statistic of the BDS test, with the residuals recovered from the linear predictive regression of excess stock returns and the partisan conflict index.