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Forecasting Equity Premium in a Panel of OECD Countries: The Role of Economic Policy Uncertainty

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Abstract

This paper investigates whether the news-based measure of economic policy uncertainty (EPU) could help in forecasting the equity premium (excess returns) in ten (Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, United Kingdom (UK), and United States (US)) Organization for Economic Co-operation and Development (OECD) countries. We analyze the monthly out-of-sample period of 2007:01-2014:12, given an in-sample period of 2003:03-2006:12, using panel data-based predictive frameworks, which controls for heterogeneity, cross-sectional dependence, persistence and endogeneity. Our results show that while, time series based predictive regression models fail to beat the benchmark of historical average, the panel data models consistently beat the benchmark in a statistically significant fashion. In general, our results highlight the importance of pooling information when trying to forecast excess stock returns based on a news-based measure of domestic EPU, as well as that of the US.

JEL Codes: C33, C53, G1

Keywords: Equity Premium, Economic Policy Uncertainty, OECD Countries, Panel Predictive Regressions

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1. Introduction

The existing international literature on forecasting stock returns (and or equity premium) is vast (Rapach et al., 2005, 2013; Sousa *et al.,* 2016; Aye et al., forthcoming a, b). Practitioners in finance require real-time forecasts of stock returns for asset allocation, and 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 (Rapach and Zhou, 2013). However, stock return forecasting is highly challenging, since it inherently contain a sizable unpredictable component. Understandably, a wide array of models (univariate and multivariate; linear and nonlinear), and predictors (domestic and international financial and macroeconomic; institutional and behavioral) have been used (see Aye *et al.,* (forthcoming a, b) and references cited therein for further details), albeit with mixed performance.

In this regard, there is a post-financial crisis, but growing, related literature that has analysed the role of uncertainty in predicting international stock returns, primarily, within-sample (see for example, Antonakakis *et al.,* (2013), Bhagat *et al.,* (2013), Kang and Ratti (2013, 2015), Gupta *et al.,* (2014), Brogaard and Detzel (2015), Chang et al., (2015), Chuliá *et al.,* (2015), Han et al., (2015), Jurado et al., (2015), Mensi *et al.,* (2014, forthcoming), Redl (2015), Sum (2012a, 2012b, forthcoming), Balcilar et al., (2015b, c, forthcoming a), Momim and Masih (2015), Rossi and Sekhposyan (2015), Li *et al.,* (2016), Antonakakis et al., (forthcoming), Aye et al., (forthcoming c), and Bekiros et al., (forthcoming a, b),). As far as out-of-sample forecasting is concerned, there are only couple of papers. While Gupta et al., (2014) failed to provide any evidence of predictability based on conditional mean-based (linear) models, Bekiros, Gupta and Majumdar (forthcoming), used a quantile predictive regression framework to show that uncertainty can forecast excess stock returns at quantiles below the median of the conditional distribution of the equity premium.

Theoretically, there are direct and indirect channels through which uncertainty can affect the stock market. In terms of the direct route, Bloom (2009) develops a standard firm-level model with a time-varying second moment of the driving process and a mix of labor and capital adjustment costs. Then the author shows that firms only hire (fire) and invest (disinvest) when business conditions are sufficiently good (bad). In addition, the model yields a central region of inaction in hiring and investment space (due to nonconvex adjustment costs), which in turn, expands when uncertainty is high, with firms becoming more cautious in responding to business conditions. This line of thinking was vindicated empirically by Kang et al., (2014). As far as the indirect channel goes, recent papers by Mumtaz and Zanetti (2013) and Carriero et al., (2015), following on the early works of Bernanke (1983), Dixit and Pindyck (1994), develop general equilibrium models to show that, besides productivity and/or policy shocks, various forms of policy-generated uncertainty leads to business cycle fluctuations.[1] And given that, asset returns are functions of the state variables of the real economy, fluctuations in it due to policy uncertainty is likely to affect the stock market.

Since uncertainty is unobservable, obtaining an appropriate measure for it is not straight-forward. Two primary approaches in this regard are: (i) News-based approach of Brogaard and Detzel (2015), and Baker et al., (2015), whereby the authors perform month-by-month searches of newspapers for terms related to economic and policy uncertainty to construct their measure of economic policy uncertainty; (ii) Alternatively, Mumtaz and Zanetti (2013), Mumtaz and Surico (2013), Alessandri and Mumtaz (2014), Mumtaz and Theodoridis (2014, 2015), Carriero et al., (2015) Jurado et al., (2015), Ludvigson et al., (2015), and Rossi and Sekhposyan (2015) recover measures of uncertainty from stochastic volatility in the error

[1] International empirical evidence on how movements in uncertainty affect economic activity can be found in: Alexopoulos and Cohen (2009), Bloom (2009), Bachmann and Bayer (2011), Knotek and Khan (2011), Aastveit et al., (2013), Bachmann et al., (2013), Colombo (2013), Jones and Olson (2013, 2015), Mumtaz and Zanetti (2013), Mumtaz and Surico (2013), Benati (2014), Karnizova and Li (2014), Alessandri and Mumtaz (2014), Balcilar et al., (2015a, forthcoming b), Caggiano et al., (2014a, 2014b, 2015), Mumtaz and Theodoridis (2015, forthcoming), Baker et al., (2015), Carriero et al., (2015), Jurado et al., (2015), Redl (2015), Rossi and Sekhposyan (2015), Sin (2015), and Netšunajev and Glass (2016).

structure of estimated structural VAR models. While there exists no clear-cut consensus in terms of which approach to use in constructing measures of uncertainty, the news-based measures of uncertainty, as developed by Baker et al., (2015), seems to have gained tremendous popularity in various applications in macroeconomics and finance.[2] This is most likely due to the fact that data (not only for the US, but also other European and emerging economies) based on this approach is easily and freely available for use, and does not require any complicated estimation of a model to generate it in the first place.

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 the news-based measure of economic policy uncertainty (EPU), introduced by Baker *et al.* (2015), could help in forecasting the equity premium (excess returns) in ten (Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, United Kingdom (UK), and United States (US)) Organization for Economic Co-operation and Development (OECD) countries. For our purpose, we analyze the monthly out-of-sample period of 2007:01-2014:12, given an in-sample period of 2003:03-2006:12, using panel data-based predictive frameworks. Specifically speaking, for the panel predictive regressions, we adopt the Common Correlated Effects (CCE) estimation method of Pesaran (2006), and the recent updates to it based on 2SLS and GMM estimation methods developed by Neal (2015) to control for possible issues of endogeneity. The issue of endogeneity is important, given that some recent evidence has emerged whereby EPU, and in general uncertainty, is believed to be driven by stock market movements and the economy as a whole (Kang and Ratti, 2013; Chang et al., 2015; Ludvigson et al., 2015). Note that, both the approaches of Pesaran (2006) and Neal (2015), not only allow for slope heterogeneity, but also controls for persistence of predictors and cross-sectional dependence.

[2] See Strobel (2015) for a detailed review of alternative measures of uncertainty.

In this regard, our contribution to the literature on stock market predictability based on uncertainty (EPU) is multi-dimensional: (i) As discussed above, the literature on out-of-sample forecasting of stock returns based on EPU is mixed and limited to only Gupta et al., (2014), and Bekiros et al., (forthcoming b), and only restricted to the US in a time series structure. Given this, our paper extends the analysis to ten developed OECD stock markets; (ii) From a methodological perspective, though we rely on a conditional mean-based approach, our analysis is based on panel data estimation over and above standard time series-based predictive regression models. As indicated by Rapach et al., (2013) and Aye et al., (forthcoming b), panel data regression tends to increases estimation efficiency relative to a time series approach, especially if the sample period is short, which happens to be the case with us, i.e., 142 observations, with an out-of-sample of 96 observations. In addition, given that our panel data estimation allows for slope heterogeneity of the EPU, over and above controlling for endogeneity, persistence and cross-sectional dependence, it does not introduce any bias in the estimation either; and, (iii) Finally, given that Ajmi et al., (2014), highlights that the EPU of the US economy drives EPU of other countries, we also analyze whether replacing the own-country EPU in the nine other OECD economies with the EPU of the US can lead to forecasting gains relative to the benchmark of historical average in both time series and panel data settings. In sum, our paper is the first paper to analyze the forecasting ability of own EPU and EPU of the US in forecasting the equity premium of major OECD stock markets using time series and panel data estimation methods. The remainder of the paper is organized as follows: Section 2 lays out the methodology, while Section 3 presents the data and the empirical results and finally, Section 4 concludes.

2. Methodology: Panel Data-Based Predictive Regression Methods

The literature on panel methods can be categorised into those that assume slope homogeneity between panel units and those that do not. The literature has shown that the presence of cross-sectional dependence in the data leads to inconsistent estimation and can cause severe bias in the estimated coefficients. In this paper we employ panel methods that allow for slope heterogeneity, correct for cross-sectional dependence, and are robust to persistency and endogeneity of the regressors.

Pesaran (2006) suggests a new approach to estimation and inference that takes into account cross sectional dependence. The proposed methodology is quite general. It allows individual specific errors to be serially correlated and heteroskedastic. Pesaran (2006) adopts a multifactor residual model:

$$ER_{jt} = \alpha_j + B_j' X_{jt-1} + e_{jt} \tag{1}$$

$$e_{jt} = \lambda_j' F_t + u_{jt}, \tag{2}$$

Where subscript *jt* denotes the observation on the jth cross section unit at time *t*, for $t = 1,2,\dots,T$ and $j = 1,2,\dots,N$. The dependent variable ER_{jt} is excess returns, while X_{jt-1} is the kx1 regressors vector, which in our case just happens to be the EPU. F_t is the mx1 vector of unobserved common factors. Note that in a time-series framework, the predictive regression framework is given by: $ER_t = \alpha + B' X_{t-1} + e_t$.

Pesaran (2006) focuses on the case of weakly stationary factors. However, more recently Kapetanios et al. (2011) formally showed that Pesaran's CCE approach continues to yield consistent estimation and valid inference even when common factors are unit root processes (I(1)). To deal with the residual cross section dependence Pesaran (2006) suggests using cross sectional averages, $\overline{ER}_t = \frac{1}{N}\sum_{j=1}^{N} ER_{jt}$ and $\bar{X}_{t-1} = \frac{1}{N}\sum_{j=1}^{N} X_{jt-1}$ as observable proxies for common factors F_t. Then, slope coefficients as well as their means, can be consistently estimated in the framework of the auxiliary regression:

$$ER_{jt} = \alpha_j + B_j' X_{jt-1} + \gamma \overline{ER}_t + \Gamma' \bar{X}_{t-1} + \varepsilon_{jt}. \tag{3}$$

Pesaran (2006) refers to the resulting OLS estimators $\hat{B}_{j,CCE-OLS}$ of the individual specific slope coefficients B_j , as the "Common Correlated Effect" (CCE) estimators:

$$\hat{B}_{j,CCE-OLS} = \left(\mathcal{X}_j' \bar{D} \mathcal{X}_j\right)^{-1} \mathcal{X}_j' \bar{D} \mathcal{ER}_j, \tag{4}$$

where $\mathcal{X}_j = \left(X_{j1}, X_{j2}, \dots, X_{jT-1}\right)'$, $\mathcal{ER}_j = \left(ER_{j2}, ER_{j2}, \dots, ER_{jT}\right)'$, $\bar{D} = I_{T-1} - \bar{H}(\bar{H}'\bar{H})^{-1}\bar{H}'$, $\bar{H} = (h_2, h_3, \dots, h_T)'$, $h_t = (1, \overline{ER}_t, \bar{X}_{t-1}{}')'$, as the "Common Correlated Effect" (CCE) estimators. The "Common Correlated Effects Mean Group" (CCEMG) estimator is the average of the individual CCE estimators $\hat{B}_{j,CCE-OLS}$:

$$\hat{B}_{CCEMG-OLS} = \sum_{j=1}^{N} \hat{B}_{j,CCE-OLS} . \tag{5}$$

The new CCEMG estimator it follows asymptotically the standard normal distribution. Specifically,

$$\sqrt{N}(\hat{B}_{CCEMG-OLS} - B) \xrightarrow{d} N(0, \Sigma_{MG}) . \tag{6}$$

The asymptotic covariance matrix Σ_{MG} can be consistently estimated by the Newey and West (1987) type procedure:

$$\hat{\Sigma}_{CCEMG-OLS} = \frac{1}{N-1} \sum_{j=1}^{N} \left(\hat{B}_{j,CCE-OLS} - \hat{B}_{CCEMG-OLS}\right)\left(\hat{B}_{j,CCE-OLS} - \hat{B}_{CCEMG-OLS}\right)' . \tag{7}$$

Pesaran (2006) focused on the case of weakly stationary factors. However, Kapetanios et al. (2011) showed that the main results of Pesaran (2006) continue to hold in the case when the unobserved factors are allowed to follow unit root processes. Their results provided support to the use of the CCE estimators irrespective of the order of integration of the data observed. In a series of Monte Carlo experiments in Pesaran (2006) and in Kapetanios et al. (2011) has been shown that the CCE estimators have the correct size, and in general have better small-sample properties than alternatives that are available in the literature. Furthermore, they have shown that small-sample properties of the CCE estimators do not seem to be much affected by the residual serial correlation of the errors.

Recently, Neal (2015) extends the CCE approach of Pesaran (2006) by replacing OLS by 2SLS/GMM using lags of the regression given in Eq.1 to form the instruments list. The author argues that the resulting CCE estimators (CCE-2SLS, CCE-GMM) as well as their mean group variants (CCEMG-2SLS, CCEMG-GMM) share the good properties of the CCE estimators of Pesaran (2006) and additionally are robust to the presence of endogenous regressors. Furthermore, Neal (2015) shows through Monte Carlo simulations that the proposed estimators demonstrate better small sample properties relative to the standard CCE estimators regardless of whether the regressors are endogenous or exogenous.

3. Data and Results

Our analysis comprises of two variables, namely, the equity premium or excess returns and the EPU. We look at ten OECD countries (Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, UK, and US) over the monthly period of 2003:03-2014:12, with the start and end date being purely driven by data availability of the EPU variable. Excess returns is defined as the stock returns (first-difference of the natural log of the stock index) in excess of a risk-free rate, which in turn, is the three-month Treasury bill rate. The data on stock index and the three-month Treasury bill rate are obtained from the macroeconomic indicators database of the OECD. The data on the EPU indices for the ten OECD countries are obtained from www.policyuncertainty.com, and is based on the work of Baker et al., (2015). The authors construct indices for major economies of the world by quantifying month-by-month searches for newspaper coverage on terms related to policy-related economic uncertainty. For inclusion in the index, the articles must contain all of the three terms of economy, policy and uncertainty simultaneously. The EPU index is converted into its natural logarithmic form. As can be seen from the summary statistics in Table 1, Germany (France) has the highest average excess returns (EPU), and Italy (Spain) has the lowest average excess returns (EPU). Italy (UK) has the highest standard deviation for the equity premium (EPU), while UK (US) has the lowest corresponding values of the standard deviation for the excess returns (EPU). Further, all excess returns are non-normal, while for the EPU of Netherlands is non-normal at the 5 percent level, and non-normality holds at the 10 percent level for Canada and UK.

We now turn our attention to the main focus of the paper, i.e., the out-of-sample forecasting of excess returns. To conduct the exercise, we split the total sample period into an in-sample period of 2003:03-2006:12, and an out-of-sample period of 2007:01-2014:12. The split is to ensure that the out-of-sample period covers the period of the financial crisis and thereafter. Note that, following the extant literature (see for example, Rapach and Zhou (2013)), the predictive regression models are estimated recursively over the out-of-sample period. We consider the following two models: Model 1: $ER_{jt} = \alpha_j + \beta_j EPU_{jt-1} + u_{jt}$, and; Model 2: $ER_{jt} = \alpha_j + \gamma_j EPU_{US,t-1} + u_{jt}$, with the benchmark being a time series random walk model with drift, i.e., historical average. We also, estimate the time series versions of Models 1 and 2, but since the focus is the panel predictive regressions, we report the time series results of these two models in the Appendix (Table A1) of the paper.

To compare the out-of-sample forecasting ability of two models, this study focuses on the relative root mean-squared error (RRMSE), i.e., the RMSE of a specific model relative to the time series random walk with drift model. To statistically assess whether the performance of alternative forecasting models outperform the historical average, we employ the McCracken's (2007) *MSE-F* test for country $j = 1,2,\ldots,N$. The *MSE-F* statistic is formally defined as

$$MSE_j - F = (T - 1 - R)\left[\frac{MSE_{b,j}}{MSE_j} - 1\right], \quad (8)$$

where R is the number of observations in the first in-sample portion, and $MSE_{b,j}$ and MSE_j are MSEs for the benchmark and the alternative forecasting models, respectively. The *MSE-F* statistic is a one-sided test for equal forecast accuracy. More specifically, *MSE-F* is formulated under the null that the forecast error from the alternative model (MSE_j) is equal to or larger than the forecast error from the benchmark ($MSE_{b,j}$). A rejection of the null indicates that the alternative model has superior forecast performance than the benchmark. The forecasting results have been presented in Table 2.

Forecasting model 1 results provide evidence that domestic EPU has strong and significant predictability of the equity premium relative to the random walk model. Additionally, the CCE-GMM estimated coefficients significantly improve the forecasting ability of the model. This is not surprising given the possible endogeneity of the regressor. In general, Model 1 with CCE-GMM individual specific coefficient estimates (INDIV) performs best. When we compare these results with Table A1, where we estimate the time series based predictive regression model with domestic uncertainty, we observe that, barring the case of Spain, the RRMSE is greater than one in all cases. Though, it is less than one for Spain, the MSE-F statistic is not significant in this case, even at the ten percent level of significance. These results are consistent with the evidence frovide for the US based on conditional mean based estimation by Gupta et al., (2014) and Bekiros et al., (forthcoming).

We next examine the forecasting ability of Model 2, which include the EPU of the US as a predictor, instead of domestic EPU, for the excess returns of the nine other OECD countries. The results have been reported in Table 2, and once again shows that EPU of the US has significant information content for forecasting equity premium of the other countries relative to the benchmark model. Though directly not comparable with Model 1 (as we have nine instead of ten countries in Model 2), but it seems that domestic uncertainty is relatively more potent in forecasting country-specific equity premium than the US uncertainty.[3] Again, when we look at the corresponding time series based predictive regression results reported in Table A1, we find no evidence of the US EPU in forecasting excess returns of the other OECD countries with the values of the RRMSE being greater than one in all cases. In sum, our results highlight the importance of pooling information, especially of domestic EPUs, using a panel data approach, and accounting for possible endogeneity of the predictor.

4. Conclusions

Theory suggests that economic uncertainty tends to affect the stock market directly and indirectly. Against this backdrop, the objective of this paper is to investigate whether news-based measure of economic policy uncertainty (EPU), could help in forecasting the equity premium in ten (Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, United Kingdom (UK), and United States (US)) Organization for Economic Co-operation and Development (OECD) countries. For our purpose, we analyze the monthly out-of-sample period of 2007:01-2014:12, given an in-sample period of 2003:03-2006:12, using panel data-based predictive frameworks that allows for heterogeneity of parameter estimates across the panels, and also account for possible issues of cross-sectional dependence, persistence and endogeneity of the predictors. Our results show that while, time series based predictive regression models fail to beat the benchmark random walk with drift (a result consistent with the literature), the panel data models consistently beat the benchmark in a statistically significant fashion. This is also true for the case when we use the EPU of the US economy in forecasting the equity premium of the nine other OECD economies. In general, our results highlight the importance of pooling information when trying to forecast excess stock returns based on a news-based measure of economic uncertainty, and simultaneously

[3] We also estimated a model that contained both domestic and US EPUs as predictors. This model outperformed Model 2 only in the case of CCE-OLS country specific coefficients (INDIV). However, model 1 and model 3 with CCE-GMM estimated coefficients seem to have similar predictive ability. Complete details of these results are available upon request from the authors.

accounting for issues of heterogeneity, cross-sectional dependence, persistence and endogeneity.

As part of future research, given that excess returns are non-normal, it would be interesting to extend the work of Bekiros et al., (forthcoming) for the US economy, based on quantile predictive regressions, to other economies. In addition, using the panel predictive framework, it would also be worthwhile to study the role of EPU in forecasting stock returns of developing countries, like the BRICS (Brazil, Russia, India, China and South Africa) for instance.

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Table 1. Summary Statistics

		Statistic									
Variables	Countries	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Observations
Excess Returns	Canada	0.0037	0.0113	0.1026	-0.2526	0.0377	-2.4001	16.7617	1256.8530	0.0000	142
	France	0.0023	0.0142	0.1008	-0.2060	0.0442	-1.4011	6.8943	136.1925	0.0000	142
	Germany	0.0055	0.0176	0.1286	-0.2382	0.0488	-1.5147	8.2931	220.0623	0.0000	142
	Italy	-0.0017	0.0085	0.1660	-0.2306	0.0521	-0.9030	6.1164	76.7600	0.0000	142
	Japan	0.0033	0.0044	0.0981	-0.2487	0.0518	-0.9073	5.6603	61.3546	0.0000	142
	Korea	0.0053	0.0136	0.1457	-0.1844	0.0478	-0.9357	5.1832	48.9192	0.0000	142
	Netherlands	0.0017	0.0111	0.0981	-0.3096	0.0497	-2.2249	13.3222	747.5644	0.0000	142
	Spain	0.0022	0.0077	0.1337	-0.1612	0.0503	-0.7894	4.1715	22.8691	0.0000	142
	UK	0.0018	0.0080	0.0844	-0.2058	0.0367	-1.7142	10.0011	359.5517	0.0000	142
	US	0.0043	0.0111	0.1184	-0.2583	0.0415	-2.1309	13.8551	804.6365	0.0000	142
EPU	Canada	4.7383	4.7503	5.9911	3.6998	0.5490	0.1662	2.0996	5.4507	0.0655	142
	France	4.9916	5.0113	5.9406	3.4217	0.5278	-0.3485	2.5304	4.1798	0.1237	142
	Germany	4.7021	4.7467	5.9345	3.3476	0.4737	-0.1919	2.8700	0.9712	0.6153	142
	Italy	4.6208	4.6394	5.4850	3.4653	0.3672	-0.2687	3.0719	1.7394	0.4191	142
	Japan	4.5579	4.5705	5.2784	3.5583	0.3634	-0.1498	2.3577	2.9720	0.2263	142
	Korea	4.6782	4.6948	5.6160	3.6107	0.4029	-0.0476	2.6802	0.6585	0.7195	142
	Netherlands	4.5138	4.5232	5.4542	3.3037	0.4316	-0.0203	2.4375	1.8817	0.3903	142
	Spain	4.5030	4.4953	6.0098	3.1492	0.4709	0.0693	3.5004	1.5951	0.4504	142
	UK	4.8974	4.9465	6.0123	3.4167	0.5864	-0.1571	2.1205	5.1611	0.0757	142
	US	4.6978	4.6318	5.5018	4.0466	0.3490	0.0976	1.9379	6.8995	0.0318	142

Note: Std. Dev. Stands for standard deviation; Probability corresponds to the Jarque-Bera test which tests the null hypothesis of normality.

Table 2: Panel Predictive Regression Forecasting Results

	CCE OLS				CCE GMM			
Country	Model 1		Model 2		Model 1		Model 2	
	INDIV	MG	INDIV	MG	INDIV	MG	INDIV	MG
Canada	0.7206***	0.8640***	0.8934***	0.9770***	0.7502***	0.7031***	0.8979***	0.8925***
France	0.7376***	0.8697***	0.9326***	0.9728***	0.6741***	0.7214***	0.9250***	0.9052***
Germany	0.7214***	0.8846***	0.9182***	0.9759***	0.7053***	0.7493***	0.9165***	0.9098***
Italy	0.7690***	0.8983***	0.8984***	0.9803***	0.7516***	0.7356***	0.8907***	0.9247***
Japan	0.7112***	0.8822***	0.8957***	0.9784***	0.7097***	0.7582***	0.8738***	0.9138***
Korea	0.7329***	0.8762***	0.8230***	0.9720***	0.7761***	0.7039***	0.8208***	0.8914***
Netherlands	0.7314***	0.8955***	0.9201***	0.9804***	0.6714***	0.7456***	0.9536***	0.9187***
Spain	0.6734***	0.8880***	0.8839***	0.9675***	0.7057***	0.7150***	0.8909***	0.9048***
UK	0.7285***	0.8657***	0.7720***	0.9816***	0.7622***	0.7219***	0.8828***	0.8946***
US	0.6677***	0.8724***			0.6837***	0.7374***		
median RRMSE	0.7250	0.8792	0.8957	0.9770	0.7078	0.7289	0.8909	0.9052
average RRMSE	0.7194	0.8797	0.8819	0.9762	0.7190	0.7292	0.8947	0.9062

Notes: The table reports the RRMSE, defined as the ratio of RMSE of a linear alternative forecasting model to that of the benchmark model (time series random walk with drift). Model 1: $ER_{jt} = \alpha_j + \beta_j EPU_{jt-1} + u_{jt}$, Model 2: $ER_{jt} = \alpha_j + \gamma_j EPU_{US,t-1} + u_{jt}$. ER_{jt} and EPU_{jt} are the excess returns and the economic policy uncertainty index of country j at time t, respectively. $EPU_{US,t}$ is the economic policy uncertainty index of the US at time t "INDIV" indicates that forecasting is based on country specific model's coefficients. "MG" indicates that forecasting is based on the average of country specific model's coefficients. *** denotes rejection of the null of equal MSEs according to the McCracken (2007) MSE-F statistic at one percent level of significance. One-step-ahead forecasts are generated recursively.

Appendix:

Table A1. Time Series Predictive Regression Forecasting Results

Country	RRMSE: Model 1	RRMSE: Model 2
Canada	1.0139	1.0169
France	1.0035	1.0114
Germany	1.0101	1.0153
Italy	1.0034	1.0103
Japan	1.0014	1.0096
Netherlands	1.0134	1.0150
South Korea	1.0050	1.0102
Spain	0.9997	1.0036
UK	1.0089	1.0174
US	1.0229	---

Note: See Notes to Table 2.