On international uncertainty links: BART-based empirical evidence for Australia

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Abstract

This project studies international uncertainty links between Australia and other countries using a Bayesian Additive Regression Trees (BART) algorithm. I use indexes of economic policy uncertainty (EPU) first developed by Baker, Bloom, and Davis (2015) to examine how EPU in Australia is linked to EPU in other countries. This project replicates research by Gupta, Pierdzioch, and Risse (2016), who studied how EPU in Canada is linked to EPU in seven other countries using a BART algorithm. Like Gupta, Pierdzioch, and Risse (2016), I utilise partial-dependence plots, relative importance measures, and permutation tests from the 'bartMachine' package in the R programming environment. I find Australian EPU is more strongly linked to the Indo-Pacific region than Anglosphere countries.

Key words: Economic policy uncertainty, BART algorithm, Australia

JEL Classification: C11, C22, D80

1 Introduction

News-based economic policy uncertainty (EPU) indexes, first developed by Baker, Bloom, and Davis (2015), are widely used in research as a measure of uncertainty. Gupta, Pierdzioch, and Risse (2016) show that interesting patterns in international uncertainty links can be explored using a BART algorithm.

The BART algorithm is a flexible, 'blackbox' algorithm with several attractive properties. It allows for nonlinearity and interaction effects between predictors and includes built-in variable selection (although the number of variables in the data set may be large, some may never appear in the internal nodes because they are 'insignificant'). By providing a predictive distribution, this Bayesian approach also enables the analysis of parameter, tree and forecast uncertainty for the response variable and the marginal effects of potential predictor variables.

Gupta, Pierdzioch, and Risse (2016) apply a BART algorithm by using the 'bartMachine' package developed by (Kapelner and Bleich, 2016) for the R programming environment to show how EPU in Canada is linked to EPU in seven other countries. I follow Gupta, Pierdzioch, and Risse (2016) methodology, but focus on Australia. Like Canada, Australia is a medium-sized, open economy that is affected directly and indirectly by global uncertainty (Kirchner, 2019). For example, between 1985 and mid-2016, only 33% of the uncertainty shocks in the US originated abroad (Bloom, 2017). In contrast, Moore (2017), who also produces an Australian uncertainty index, shows that about 90% uncertainty shocks over this period emerged from overseas.

Research has shown that domestic EPU adversely affects Australian acquisition (Shams, Gunaskerage, and Velayutham, 2022) and capital investment (Chen et al., 2020) outcomes. However, there is limited research on Australia's international uncertainty links. Further, the BART algorithm accounts for nonlinearity and interaction effects between predictors, which illuminates an alternative perspective on the quantitative importance of international uncertainty links.

Section 2 describes the data used. In Section 3, I describe the BART algorithm. Section 4 summarises the empirical results, and I conclude in Section 5.

2 The data

I study two datasets summarised in Table 1. The Australian EPU index is available from January 1997 to April 2022. Dataset 1 includes all countries where data are available for this period at the time of writing (May 2022). Dataset 2 includes observations from January 2003 to December 2020. The shorter time series is due to less data availability for the three additional countries included in dataset 2: Hong Kong, Singapore and New Zealand.

Table 1: Sample period and variables in each dataset

	Dataset 1	Dataset 2
Sample period	1997M1 to 2022M4	2003M1 to 2020M12
Response variable	Australia	Australia
Predictor variables	Brazil	Brazil
	Canada	Canada
	Chile	Chile
	Colombia	Colombia
	France	France
	Germany	Germany
	Greece	Greece
	India	India
	Ireland	Ireland
	Italy	Italy
	Japan	Japan
	Korea	Korea
	Netherlands	Netherlands
	Russia	Russia
	Spain	Spain
	UK	UK
	US	US
	Mainland China	Mainland China
		Singapore
		Hong Kong
		New Zealand

The EPU indexes are at a monthly frequency. Like Ajmi, Gupta, and Kanda (2014) and Gupta, Pierdzioch, and Risse (2016), all indexes are transformed by taking the natural log, followed by demeaning the data.

All country EPU indexes are based on methodologies similar to Baker, Bloom, and Davis (2015), who search for newspaper articles containing:

- the terms "uncertainty" or "uncertain"
- the terms "economic" or "economy"
- and any monetary or fiscal policy-related terms

The newspaper article must include terms from all three categories above for inclusion in the index. For specific methodologies, see country sources in Table 3 in the Appendix.

3 The BART algorithm

A Bart model uses a likelihood function and a prior, just like any other Bayesian model. A Bayesian backfitting algorithm is then applied using the ‘bartMachine’ package in R to generate draws from the posterior distribution[1].

3.1 The likelihood function

The likelihood in BART is a sum-of-trees model. I use a sum-of-trees model proposed by Chipman, George, and McCulloch (2010), where the idea is to model the EPU index for Australia, Y_n, by summing all the Bayesian regression trees in the following format:

$$Y_n = \sum_{j=1}^{m} g(x_n|T_j, M_j) + \epsilon_n, \epsilon_i \overset{iid}{\sim} N(0, \sigma^2) \tag{1}$$

In Equation 1, BART seeks to approximate $g(.)$ using regression trees, where predictor countries, x_n, might contain many variables. T_j denotes a tree consisting of a set of internal node decision rules and a set of terminal nodes. M_j are its associated terminal node parameters.

Splitting rules divide the space of predictor countries, x_n, into different intervals, known as internal nodes or ‘branches’. For example, the terminal node parameter, μ_1, predicts the EPU index for Australia, when $x_n \leq c$ and the terminal node parameter, μ_2, predicts the EPU index for Australia when $x_n \geq c$, where c is a threshold value within the range of values of the predictor variable x_n. Observations are allocated to subgroups by dropping them down the tree and sending them left or right, in accordance with the splitting rule at each interior node. Splitting observations at each interior node continues iteratively until a terminal node is reached, which are the terminal node parameters.

3.2 The prior

Large tree models tend to overfit the data, that is, they fit the noise in the data, rather than detecting a pattern. To overcome this problem, a prior is employed to stop the trees from overfitting. A prior for the BART has three components:

1. The tree structure $p(T_j)$, which is chosen to enforce shallow tree structures by restricting the complexity of a single tree. This is done to prevent overfitting. Chipman, George, and McCulloch (1998) set the prior probability that a node will split (i.e. is not a terminal node), as given in Equation 2.

$$\alpha(1 + d)^{-\beta}, \alpha \in (0, 1), \beta \in [0, \infty) \tag{2}$$

Where d = depth of the tree (the number of times a node is splitting rule and not a terminal node), α controls the strength of prior, and β controls how fast the probability

[1]My code for this project is available on my GitHub.

decreases in d that a node is nonterminal. I use the default parameters recommended by Chipman, George, and McCulloch (2010) where $\alpha = 0.95$ and $\beta = 2$. [2]

2. The terminal node parameters conditional on the tree structure $p(M_j|T_j)$, which limits the effect of the individual tree components by keeping them small. The prior on each terminal node parameter is given by $N(\mu_\mu/m, \sigma_\mu^2)$, with an expected value, μ_μ, of $(y_{max}+y_{min})/2)$. As m is the number of trees, σ_μ^2 is the prior parameter, which Kapelner and Bleich (2016) chooses such that $m\mu_\mu - k\sqrt{m}\sigma_\mu = y_{min}$ and $m\mu_\mu + k\sqrt{m}\sigma_\mu = y_{max}$ for some k. Higher values of k result in stronger model regularisation by reducing the size of σ_μ^2.

3. The final prior is for the error variance $p(\sigma^2)$. Following Gupta, Pierdzioch, and Risse (2016), the inverse gamma distribution $\text{InvGamma}(v/2, v\lambda/2)$ is used for $p(\sigma^2)$. The parameter, λ, is determined by the data such that there is a priori qth-percentage chance that the BART model will improve the RMSE of a least squares regression Kapelner and Bleich (2016). This prior also limits overfitting by restricting the probability mass placed on small values of σ^2.

The error variance, $p(\sigma^2)$ is assumed to be independent of the tree structure and terminal node parameters. Therefore, the prior can be written as:

$$= [\Pi_j \; p(M_j|T_j) \; p(T_j)] \; p(\sigma^2) \tag{3}$$

In addition to the number of trees m that must be chosen, the adjustable parameters are now α, β, k, q, and v. To prevent overfitting, I employ the parameters used by Gupta, Pierdzioch, and Risse (2016), who use a conservative setup advocated by Chipman, George, and McCulloch (2010) where: $\alpha = 0.95$, $\beta = 2$, $m = 200$, $k = 5$, $q = 0.75$ and $v = 10$.

3.3 bartMachine

With the priors specified, 'bartMachine' uses a Metropolis-within-Gibbs sampler (S. Geman and D. Geman, 1984; Hastings, 1970) to generate draws from the posterior distribution of the sum of trees function in Equation 1 (Kapelner and Bleich, 2016). An important characteristic of this sampler for BART is that it uses a form of Bayesian backfitting (Hastie and Tibshirani, 2000), which works as follows:

1. Fit the jth tree, T_j, iteratively, holding the other $m-1$ trees constant, to the partial residuals that result when T_j is excluded. A new tree structure is then proposed, which is accepted or rejected by a Metropolis–Hastings algorithm.

2. Given the new structure, samples from the posterior of the terminal node parameters are then drawn, completing the new estimate of T_j.

3. Using the updated set of partial residuals, steps 1 and 2 are repeated iteratively for each tree.

[2] In the Gupta, Pierdzioch, and Risse (2016) paper, they say they use $\alpha = 2$ and $\beta = 0.95$, but this looks like a typo and should be the other way around as $\alpha \in (0, 1)$.

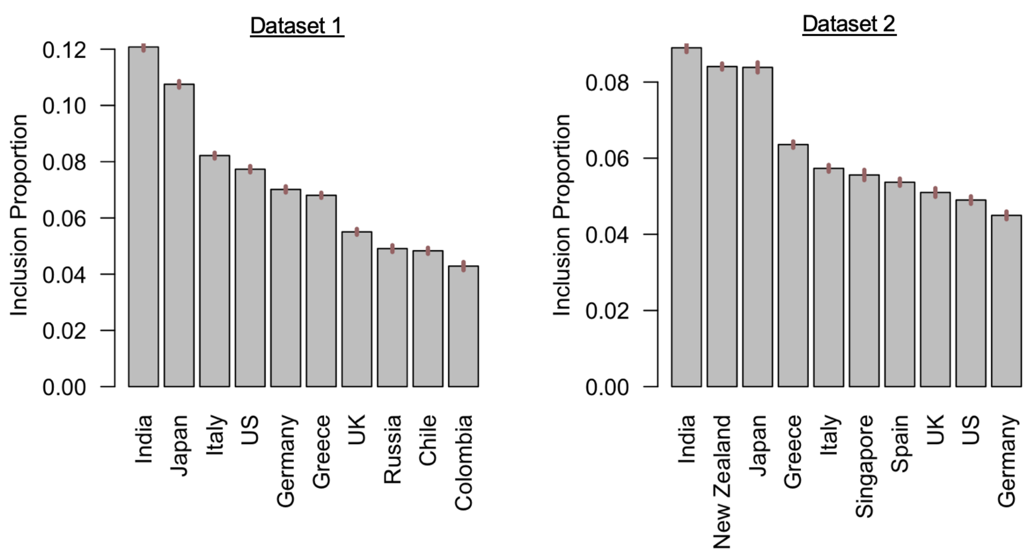
4. A draw from the posterior of the variance parameter, σ^2, is conducted based on the full model residuals, conditional on the updated set of tree structures and the terminal node parameters.

Steps 1 to 4 are simulated 3000 times, which provides draws from the posterior for the sum-of-trees function. I follow Gupta, Pierdzioch, and Risse (2016) and use 3000 simulation runs of the Bayesian MCMC backfitting algorithm, and discard the first 2000 burn-in runs. The average over the draws gives the posterior mean estimate of the Australian EPU index, where the dispersion of the draws is used for inferential purposes.

4 Empirical results

Figure 1 summarises the relative importance (in percent) of the top 10 predictors in dataset 1 and dataset 2. Almost all relative importance percentages are smaller in dataset 2 than dataset 1 because of the inclusion of more predictors. The inclusion proportion for a particular predictor is the percentage of times that country is picked as a splitting rule among all splitting rules in the posterior draws of the sum-of-trees model (Kapelner and Bleich, 2016).

Figure 1: Top 10 countries by relative importance (in percent)



In both datasets, the EPU index for India is the top splitting variable, with a relative importance of 12% in dataset 1 and 9% in dataset 2. This is a surprising result, but India has increased in terms of its global economic prominence. Furthermore, people movements and trade flows between Australia and India have increased in recent decades.

New Zealand is only included in dataset 2 and is the second highest splitting variable, with a relative importance of 8%. This is expected, given the two economies share similar characteristics, are geographically close to one another, and are the most economically integrated with one another. Japan is the second highest splitting variable in dataset 1 and the third highest splitting variable in dataset 2, with a relative importance of 11% and 8%, respectively. Japan was Australia's largest trading partner from 1967 until 2007. It remains Australia's third-largest trading partner, and was the second-largest direct foreign investor in Australia in 2020 (*Japan Country Brief* 2021).

At first glance, the inclusion of Greece, Italy and Germany in the top 10 of both datasets appears surprising. A possible explanation is that these countries were the most prominent during the Eurozone crisis, which dominated (and caused) much economic uncertainty in the early part of the last decade. A key finding from Gupta, Pierdzioch, and Risse (2016) was that the EPU indexes for the United Kingdom and the United States were the top splitting variables for Canada, while Klößner and Sekkel (2014) find that the United Kingdom and the United States are important exporters of international uncertainty spillover effects. My finding suggest the UK and US are not as important to Australia as Canada. The United States and United Kingdom remain in the top 10 predictors in dataset 1 and dataset 2 for Australia, but are much lower than what Gupta, Pierdzioch, and Risse (2016) finds for Canada and what one might expect given the close cultural and historical ties. Overall, this suggests Australian EPU is more strongly linked to the Indo-Pacific region than the

Anglosphere countries.

Table 2 summarizes the significance of the predictor countries and the overall fit of the model. The significance of predictors is assessed using permutation tests, where the null hypothesis of the permutation test is that a predictor country does not have explanatory power for Australian EPU. The p-values for BART in dataset 1 yield significant results for Germany, Greece, India, Italy, Japan, Russia (<1%) and the US (<5%). The p-values for BART in dataset 2 yield significant results for Chile, Greece, India, Italy, Japan, New Zealand, (<1%) and Russia (<5%).

Table 2: Significance of predictors and model fit

Country	Dataset 1		Dataset 2	
	p-value BART	p-value OLS	p-value BART	p-value OLS
Brazil	0.7619	0.1229	0.2857	0.0582*
Canada	0.9048	0.3245	0.1429	0.7347
Chile	0.1429	0.0414**	0.0000***	0.0166**
Colombia	0.5714	0.2475	0.2381	0.0114**
France	0.6667	0.2066	0.7619	0.0328**
Germany	0.0000***	0.0130**	0.1429	0.8648
Greece	0.0000***	0.0063***	0.0000***	0.0008***
India	0.0000***	0.0000***	0.0000***	0.0000***
Ireland	0.7143	0.8249	0.3333	0.3192
Italy	0.0000***	0.3184	0.0000***	0.3302
Japan	0.0000***	0.0002***	0.0000***	0.0102**
Korea	0.7143	0.1436	0.9048	0.2173
Netherlands	0.8095	0.2796	0.1429	0.1194
Russia	0.0000***	0.4811	0.0476**	0.2763
Spain	0.6190	0.0963*	0.1905	0.1154
UK	0.5238	0.0245**	0.2381	0.0237**
US	0.0476**	0.0008***	0.2381	0.1075
Mainland China	0.7143	0.1387	0.2381	0.0027***
New Zealand			0.0000***	0.0164**
Hong Kong			0.1429	0.6082
Singapore			0.1905	0.0200**
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$				
Overall significance	0.0000	0.0000	0.0000	0.0000
Shapiro-Wilk (p-value)	0.8901	0.5424	0.2208	0.7821
Pseudo-/Adjusted-)R^2	0.7956	0.7329	0.8609	0.8017

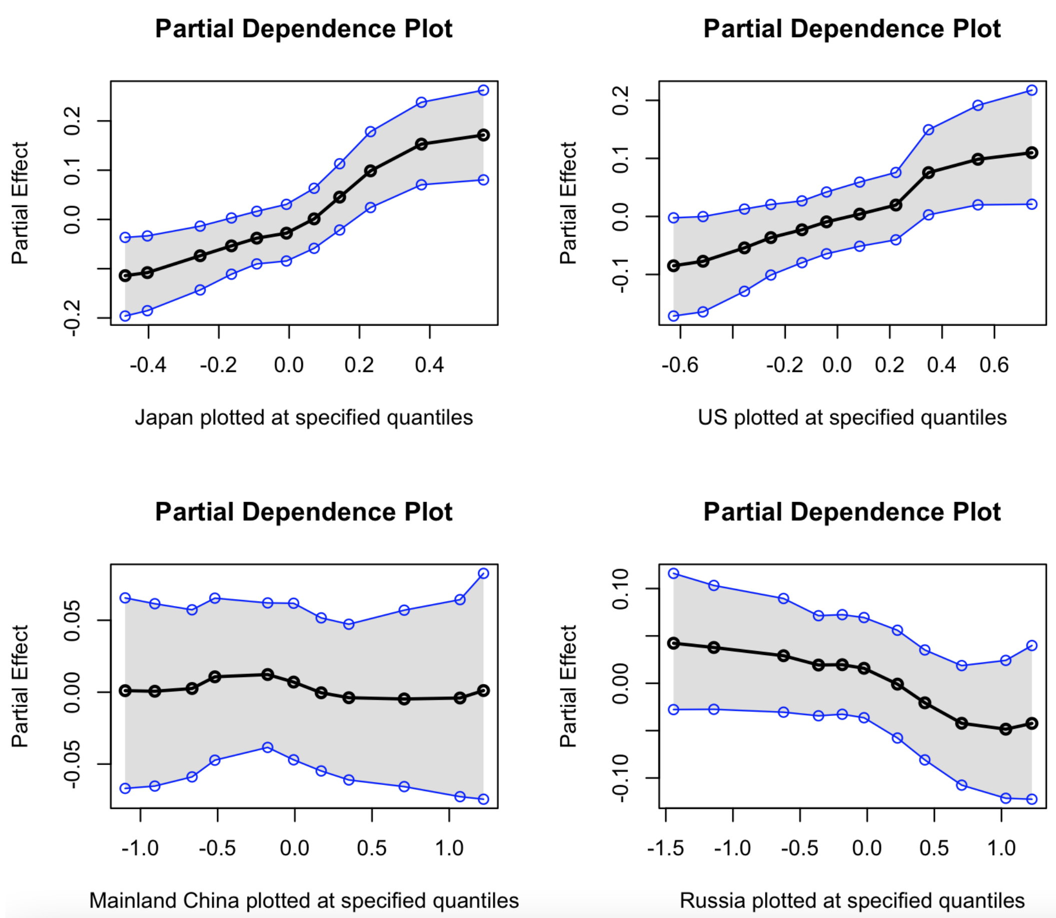
Note: p-values for BART are tests of covariate importance conditional on the cross-validated bartMachine model. All tests are performed with 20 null samples. Overall significance summarises the result of a joint permutation test for the BART result. The null hypothesis of the Shapiro-Wilk test is that the residuals have a normal distribution. OLS p-values are robust to heterscedasticity and autocorrelation (using a HAC covariance matrix). Overall significance for the OLS model summarises the results of an F-test.

For both dataset 1 and dataset 2, the findings of the joint permutation test for all predictors are very significant, while the Shapiro–Wilk test indicates that the residuals' normality cannot be rejected. The BART algorithm provides a decent model fit, as shown by the

Pseudo-R^2, which assumes values of 0.80 and 0.86 for datasets 1 and 2, respectively. Similar to Gupta, Pierdzioch, and Risse (2016), I also provide results for a regular OLS model for comparison. The OLS model detects the linear effects in India and New Zealand. However, in Italy, for example, the OLS model does not recover the nonlinear relationships, while the overall fit is slightly worse for the OLS models.

Figure 2 shows select partial dependence plots for selected countries in dataset 1, which displays the marginal effect of a predictor on the Australia EPU index, keeping the other predictors fixed. The international uncertainty link is linear, but less than proportional, for the United States and Japan, while it is downward sloping for Russia, suggesting the Australian EPU index reacts positively for a negative log EPU index in Russia. The partial dependence plots confirm that Mainland China is relatively insignificant, as is also evident in Table 2 and Figure 1, with a small, flat partial effect.

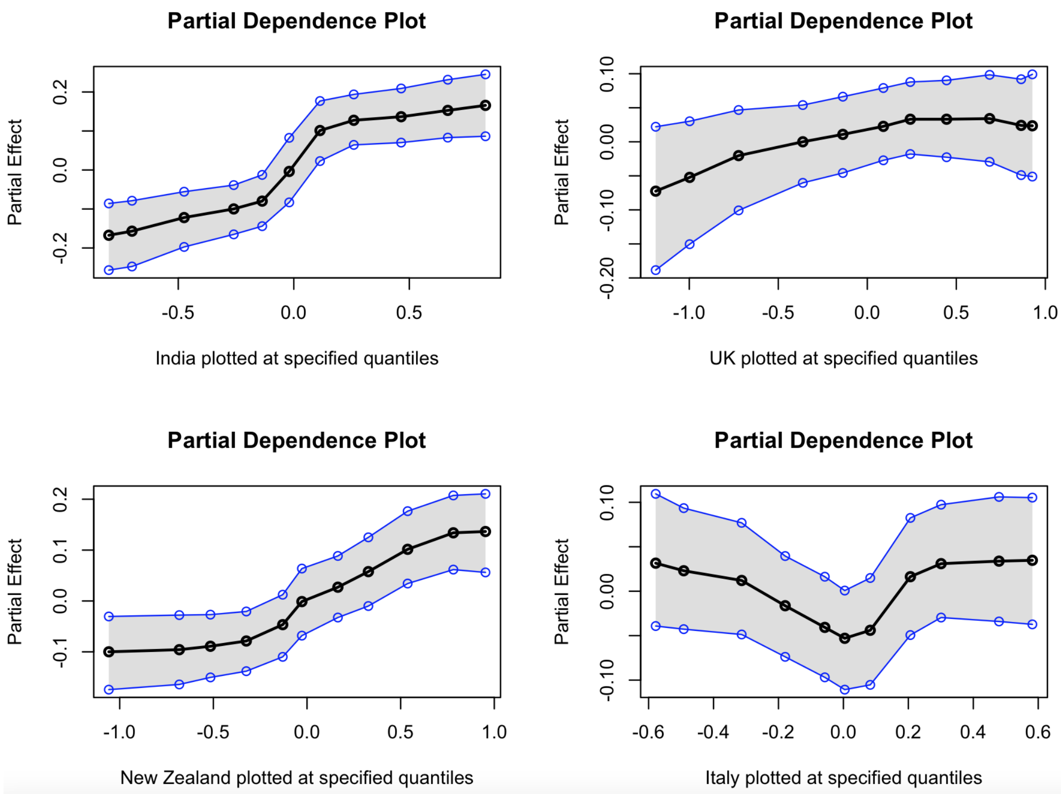
Figure 2: Partial dependence plots for selected countries in dataset 1



Notes: Blue lines are the 95% interval of the posterior that are based on 1000 draws from the posterior.

Figure 3 shows select partial dependence plots for selected countries in dataset 2. The international uncertainty link for New Zealand is upward sloping and linear, but less than proportional. India follows a similar pattern, but there is a large kink around 0, indicating that the Australian EPU does change significantly for small changes around 0 of the log EPU index for India. The UK appears to show an asymmetric international uncertainty link with Australia, where the Australian EPU does not change significantly for a positive log EPU index for the UK, but the Australian EPU index decreases as the log of the UK EPU index becomes negative. Italy displays a U-shape, which explains why the EPU index for Italy is an important predictor using BART, but not OLS. This is because BART takes into account nonlinearity and interaction effects, which OLS does not.

Figure 3: Partial dependence plots for selected countries in dataset 2



Notes: Blue lines are the 95% interval of the posterior that are based on 1000 draws from the posterior.

5 Conclusion

BART is a useful technique that quantifies the relative importance of uncertainty links and provides significant variable testing that is simple. I find Australian EPU is more strongly linked to EPU in the Indo-Pacific region than the Anglosphere countries. This analysis could be expanded in many ways. First, the study could be extended to incorporate alternative uncertainty measures like geopolitical risk, trade and climate policy uncertainty or financial stress[3]. Second, predictor lags could be included to better understand the dynamic interplay between uncertainty measures. Third, it would be useful to see how uncertainty spillover links change over time. Fourth, cross validation could be used to find more optimal values for the parameters.

[3] All available at www.policyuncertainty.com.

References

Ajmi, Ahdi Noomen, Rangan Gupta, and Patrick Kanda (Apr. 2014). *Causality between Economic Policy Uncertainty Across Countries: Evidence from Linear and Nonlinear Tests.* SSRN Scholarly Paper 2558760. Rochester, NY: Social Science Research Network (cit. on p. 3).

Baker, Scott, Nicholas Bloom, and Steven Davis (Oct. 2015). *Measuring Economic Policy Uncertainty.* NBER Working Paper 21633. National Bureau of Economic Research, Inc (cit. on pp. 1–3).

Bloom, Nicholas (2017). "Observations on Uncertainty". In: *Australian Economic Review* 50.1, pp. 79–84. ISSN: 1467-8462. DOI: 10.1111/1467-8462.12203 (cit. on p. 2).

Chen, Xikai et al. (June 2020). "Australian Policy Uncertainty and Corporate Investment". In: *Pacific-Basin Finance Journal* 61, p. 101341. ISSN: 0927-538X. DOI: 10.1016/j.pacfin.2020.101341 (cit. on p. 2).

Chipman, Hugh A., Edward I. George, and Robert E. McCulloch (Sept. 1998). "Bayesian CART Model Search". In: *Journal of the American Statistical Association* 93.443, pp. 935–948. ISSN: 0162-1459, 1537-274X. DOI: 10.1080/01621459.1998.10473750 (cit. on p. 4).

– (Mar. 2010). "BART: Bayesian Additive Regression Trees". In: *The Annals of Applied Statistics* 4.1. ISSN: 1932-6157. DOI: 10.1214/09-AOAS285 (cit. on pp. 4, 5).

Geman, Stuart and Donald Geman (Nov. 1984). "Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* PAMI-6.6, pp. 721–741. ISSN: 1939-3539. DOI: 10.1109/TPAMI.1984.4767596 (cit. on p. 5).

Gupta, Rangan, Christian Pierdzioch, and Marian Risse (June 2016). "On International Uncertainty Links: BART-based Empirical Evidence for Canada". In: *Economics Letters* 143, pp. 24–27. ISSN: 0165-1765. DOI: 10.1016/j.econlet.2016.03.009 (cit. on pp. 1–3, 5–7, 9).

Hastie, Trevor and Robert Tibshirani (Aug. 2000). "Bayesian Backfitting (with Comments and a Rejoinder by the Authors". In: *Statistical Science* 15.3, pp. 196–223. ISSN: 0883-4237, 2168-8745. DOI: 10.1214/ss/1009212815 (cit. on p. 5).

Hastings, W. K. (1970). "Monte Carlo Sampling Methods Using Markov Chains and Their Applications". In: *Biometrika* 57.1, pp. 97–109. ISSN: 0006-3444. DOI: 10.2307/2334940 (cit. on p. 5).

Japan Country Brief (2021). https://www.dfat.gov.au/geo/japan/japan-country-brief (cit. on p. 7).

Kapelner, Adam and Justin Bleich (2016). "**bartMachine** : Machine Learning with Bayesian Additive Regression Trees". In: *Journal of Statistical Software* 70.4. ISSN: 1548-7660. DOI: 10.18637/jss.v070.i04 (cit. on pp. 2, 5, 7).

Kirchner, Stephen (2019). "State of Confusion: Economic Policy Uncertainty and International Trade and Investment". In: *Australian Economic Review* 52.2, pp. 178–199. ISSN: 1467-8462. DOI: 10.1111/1467-8462.12319 (cit. on p. 2).

Klößner, Stefan and Rodrigo Sekkel (2014). "International Spillovers of Policy Uncertainty". In: *Economics Letters* 124.3, pp. 508–512. ISSN: 0165-1765 (cit. on p. 7).

Moore, Angus (Dec. 2017). "Measuring Economic Uncertainty and Its Effects". In: *Economic Record* 93.303, pp. 550–575. ISSN: 00130249. DOI: 10.1111/1475-4932.12356 (cit. on p. 2).

Shams, Syed, Abeyratna Gunaskerage, and Eswaran Velayutham (Mar. 2022). "Economic Policy Uncertainty and Acquisition Performance: Australian Evidence". In: *International*

Review of Economics & Finance 78, pp. 286–308. ISSN: 1059-0560. DOI: 10.1016/j.iref.2021.12.004 (cit. on p. 2).

Appendix

Table 3: EPU index data references by country

Country	**Source**
Australia	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Brazil	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Canada	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Chile	Cerda, R., A. Silva and J. T. Valente, 2016. “Economic Policy Uncertainty Indices for Chile,” working paper.
Colombia	Gil, M. and D. Silva, 2018. “Economic Policy Uncertainty Indices for Colombia,” working paper.
France	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Germany	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Greece	Hardouvelis, G. A., G. I. Karalas, D. I. Karanastasis and P. K. Samartzis, 2018. “Economic Policy Uncertainty, Political Uncertainty and the Greek Economic Crisis,” working paper, May.
India	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Ireland	Zalla, R., 2016. “Economic Policy Uncertainty in Ireland,” working paper, 20 September.
Italy	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Japan	”Policy Uncertainty in Japan” by Elif C. Arbatli Saxegaard, Steven J. Davis, Arata Ito, and Naoko Miake.
Korea	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Netherlands	Kroese, L., S. Kok and J. Parlevliet, 2015. “Beleidsonzekerheid in Nederland,” Economisch Statistische Berichten, No. 4715, pp. 464–467.
Russia	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Spain	Ghirelli, C., J.J. Perez, and A. Urtasun, 2019. “A New Economic Policy Uncertainty Index for Spain,” Bank of Spain, WorkingPaper No., 1906.

UK	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
US	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
Mainland China	Baker, S. R., N. Bloom, and S. J. Davis, 2016. “Measuring Economic Policy Uncertainty,” Quarterly Journal of Economics, 131, no. 4 (November), 1593-1636.
New Zealand	Ali, S., Badshah, I., Demirer, R., & Hegde, P., 2022. ”Economic Policy Uncertainty and Institutional Investment Returns: The Case of New Zealand,” Available at SSRN:https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4073046
Hong Kong	Luk, P., Cheng, M., Ng, P., Wong, K., 2017. ”Economic Policy Uncertainty Spillovers in Small Open Economies: the case of Hong Kong”
Singapore	Davis, S. J., 2016. “An Index of Global Economic Policy Uncertainty.” Macroeconomic Review, October. Also available as NBER Working Paper No. 22740.