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Modeling the presidential approval ratings of the United States using machine-learning : does climate policy uncertainty matter?

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Modeling the Presidential Approval Ratings of the United States using Machine-Learning: Does Climate Policy Uncertainty Matter?

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Modeling the Presidential Approval Ratings of the United States using Machine-Learning: Does Climate Policy Uncertainty Matter?

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Abstract

In the wake of a massive thrust on designing policies to tackle climate change, we study the role of climate policy uncertainty in impacting the presidential approval ratings of the United States (US). We control for other policy related uncertainties and geopolitical risks, over and above macroeconomic and financial predictors used in earlier literature on drivers of approval ratings of the US president. Because we study as many as 19 determinants, and nonlinearity is a well-established observation in this area of research, we utilize random forests, a machine-learning approach, to derive our results over the monthly period of 1987:04 to 2023:12. We find that, though the association of the presidential approval ratings with climate policy uncertainty is moderately negative and nonlinear, this type of uncertainty is in fact relatively more important than other measures of policy-related uncertainties, as well as many of the widely-used macroeconomic and financial indicators associated with presidential approval. In addition, and more importantly, we also detect that the importance of climate policy uncertainty has grown in recent years in terms of its impact on the approval ratings of the US president.

JEL Classifications: C22; Q54.

Keywords: Presidential approval ratings; Climate policy uncertainty; Random forests

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1 Introduction

Climate change certainly is among the most widely-recognized challenges that we as human beings are facing currently, as it has the potential to affect negatively the health and well-being of a large proportion of the world population and, thereby, poses a large aggregate risk to the economy (Giglio et al., 2021). In the fight against climate change, environmental policies aiming at reducing greenhouse gases (GHGs) play a key role. In the United States (US), being the second largest emitter of greenhouse gases (GHGs) after China,¹ environmental policies have aimed at addressing climate change by reducing GHGs for quite a few decades now, especially since the administration of President William (Bill) J. Clinton, starting in 1993. Yet, there has been substantial uncertainty regarding the specific implementation paths of such policies across Democratic and Republican presidents. With the US going into elections at the end of this year, a pertinent question to ask would be: Does uncertainty around climate-related policies impact the presidential approval ratings?

We address this question econometrically by analyzing the association of a metric of climate policy uncertainty and approval ratings of US presidents during the monthly period of 1987:04 to 2023:12, where we control for other forms of policy-related uncertainties as well as geopolitical risks, over and above macroeconomic and financial conditions studied in earlier literature on drivers of US presidential approval ratings (see, Choi et al. (2016), Gupta et al. (2021, 2023), and Chen et al. (2023) for detailed reviews).² Because our analysis involves a total of 19 impact variables (including the lagged presidential approval ratings), we shed light on the link between US presidential approval ratings and climate policy uncertainty by means of a machine-learning approach known as random forests (Breiman, 2001). Random forests can accurately trace out the link between presidential approval ratings and a large number of its drivers in a full-fledged data-driven manner. Importantly, random forests automatically capture potential nonlinear links between the US presidential approval ratings and climate policy uncertainty and the various other control variables. The importance of nonlinearities has been emphasized by Halcoussis et al. (2009), Choi et al. (2016), and Gupta et al. (2021) in their studies of the link between movements in presidential approval rating with macroeconomic and financial variables. As

¹See: <https://globalcarbonatlas.org/emissions/carbon-emissions/>.

²While the period of study is purely driven by the availability of data on climate policy uncertainty, the sample period allows the terms of four Republican and three Democratic presidents to be covered.

our empirical results show, a nonlinear link of US presidential approval ratings is strongly present with climate policy uncertainty as well.

To the best of our knowledge, we are the first to analyze the role of climate policy uncertainty, over and above a host of other macroeconomic and financial variables, policy-related uncertainties, and geopolitical risks, in driving US presidential approval ratings using a machine-learning approach. The remaining sections of our paper are structured as follows: In Section 2, we provide a description of the data we used in our study, while we outline in Section 3 our econometric model. We present our results in Section 4. Finally, we conclude our paper in Section 5.

2 Data

The data on presidential approval ratings (*PAR*) are based on surveys conducted by Gallup, as part of the American Presidency Project.³ A rating, which is commonly expressed in percentage terms, informs about the proportion of respondents to an opinion poll who approve of the US president in office when the poll was conducted. In contrast to other national polls informing about public approval of the president, the Gallup poll has been based over the years (since, July, 1941) on the same approval question: “Do you approve or disapprove of the way [enter president name] is handling his job as president?”

As far as our main predictor, i.e., climate policy uncertainty (*CPU*) is concerned, we rely on the index developed by Gavrilidis (2021), who focuses on scaled frequency, i.e., percentage, of climate policy-related articles to total number of articles from eight leading US newspapers⁴ that include the terms “uncertainty” or “uncertain” and “carbon dioxide” or “climate” or “climate risk” or “greenhouse gas emissions” or “greenhouse” or “CO₂” or “emissions” or “global warming” or “climate change” or “green energy” or “renewable energy” or “environmental” and “regulation” or “legislation” or “White House” or “Congress” or “EPA” or “law” or “policy”.⁵

The categorical data involving policy related uncertainties consists of a range of sub-

³The data is publicly available for download from: <http://www.presidency.ucsb.edu/data/popularity.php>.

⁴Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal.

⁵For a description of the data and the data itself, see the internet page https://policyuncertainty.com/climate_uncertainty.html.

indexes of Baker et al.'s (2016) overall economic policy uncertainty (*EPU*) index, based solely on news data. The sub-indexes are derived using results from the Access World News database of over 2,000 US newspapers. Every sub-index requires an article published in these newspapers to contain the terms “uncertainty” or “uncertain”, “economic” or “economy”, and one or more of the terms “congress”, “legislation”, “white house”, “regulation”, “federal reserve”, or “deficit”, as well as a set of categorical policy terms associated with monetary policy, taxes, government spending, health care, national security, entitlement programs, regulation, financial regulation, trade policy, and sovereign debt and currency crises.⁶

As far as sub-indexes of geopolitical risks due to threats and attacks are concerned, they are based on the work of Caldara and Iacoviello (2022).⁷ They construct the indexes by counting the number of articles related to adverse geopolitical events using automated text search of the electronic archives of 10 newspapers⁸ for each month (as a share of the total number of news articles). The search spans eight categories (war threats, peace threats, military buildups, nuclear threats, terror threats, beginning of war, escalation of war, terror acts), with the geopolitical threats (*GPRT*) index covering categories 1 to 5, and the geopolitical acts (*GPRA*) index covering categories 6 to 8. It should be noted that our decision to use geopolitical risks due to threats and actual attacks as our additional controls emanate from the fact that our sample period does include quite a few events of such uncertainties involving the US directly, and indirectly (due to the position taken by the government on regional conflicts not involving the US per se), which is known to shape public opinion, and understandably approval ratings of the president in office during those periods.

In line with earlier literature on the macroeconomic and financial controls driving the *PAR*, we first use the the Chicago Fed National Activity Index (*CFNAI*) defining macroeconomic conditions, which is a weighted average of 85 monthly indicators of national economic activity derived from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders,

⁶The reader is referred to: http://policyuncertainty.com/categorical_terms.html for complete details on the term sets by category of *EPU*. The ten categorical sub-indexes are available for download from: http://policyuncertainty.com/categorical_epu.html.

⁷The data can be downloaded from: <https://www.matteoiacoviello.com/gpr.htm>.

⁸Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post

and inventories.⁹ In this regard, we also utilize the year-on-year consumer price index (*CPI*)-based inflation rate (*Inflation*), and stance of monetary policy ($FRR + SSR$) as captured by the Federal Funds Rate (*FRR*) merged with the Shadow Short Rate (*SSR*) of Wu and Xia (2016), with the latter capturing unconventional monetary policy decisions when the *FRR* reaches its zero lower bound.¹⁰ The financial state of the economy is captured by using the Chicago Fed’s National Financial Conditions Index (*NFCI*), which, in turn, provides a comprehensive weekly update on US conditions in money markets, debt and equity markets, and the traditional and “shadow” banking systems.¹¹

Based on the availability of the *CPU* index, our monthly sample period ranges from 1987:04 to 2023:12, covering the partial presidential terms of Ronald W. Reagan (January 20, 1981–January 20, 1989; Republican) and Joseph (Joe) R. Biden Jr. (January 20, 2021–to date; Democratic), and the complete terms of George H.W. Bush (January 20, 1989–January 20, 1993; Republican), William (Bill) J. Clinton (January 20, 1993–January 20, 2001; Democratic), George W. Bush (January 20, 2001–January 20, 2009; Republican), Barack H. Obama II (January 20, 2009–January 20, 2017; Democratic), and Donald J. Trump (January 20, 2017–January 20, 2021; Republican). In essence, we cover seven presidents, with four belonging to the Republican party and three to the Democratic party, with nearly a 50% split (213 (Republican) versus 228 (Democratic)) of the time in office of the 441 months of data under investigation.

3 Method

Our main empirical model expresses the presidential approval ratings (*PAR*) as a function of its lagged realization, climate policy uncertainty (*CPU*), and a vector (X_t) of control variables, which basically includes the ten categorical policy uncertainty indexes, two geopolitical risks indexes, a national activity index, the inflation rate, a uniform metric of conventional and unconventional monetary policies, and a financial conditions index, as

⁹The data is freely available at: <https://www.chicagofed.org/research/data/cfnai/current-data>.

¹⁰The *CPI* and *FRR* data are obtained from the FRED database maintained by the St. Louis Fed, while the *SSR* is downloadable from: <https://sites.google.com/view/jingcynthiawu/shadow-rates?authuser=0>.

¹¹The weekly data, which is averaged to monthly frequency, can be retrieved from: <https://www.chicagofed.org/research/data/nfci/current-data>.

outlined in Section 2. The empirical model is given by the following equation:

$$PAR_t = f(PAR_{t-1}, CPU_t, X_t) \quad (1)$$

where f denotes the function to be estimated. Given that we have in total 19 left-hand-side predictor variables, we estimate the function, f , by means of random forests (Breiman, 2001), a machine-learning technique that combines in an additive way an ensemble of m individual regression trees to compute an approximation of the function, f in a data-driven manner as follows:

$$f(PAR_{t-1}, CPU_t, X_t) = \sum_k T_k, \quad k = 1, 2, \dots, m. \quad (2)$$

An individual regression tree, T_k , consists of nodes and branches that partition the space of the predictors into l non-overlapping regions, R_l , which are computed by invoking a search-and-split algorithm in a recursive top-down way (Breiman et al., 1983). In order to illustrate how this algorithm works, it is instructive to start at the root of a regression tree, where we initialize the growth of a tree by subdividing the space of predictors into a left region (i.e., a branch), R_1 , and a right region, R_2 . These two regions are formed optimally by iterating over the predictors and by using (in the simplest case) every realization of a predictor as a candidate splitting point. In this way, we obtain combinations of a predictor and a splitting point, $\{s, p\}$, which we then can use to define the left and right regions, $R_1(s, p) = \{z_s | z_s \leq p\}$ and $R_2(s, p) = \{z_s | z_s > p\}$, where $z = \text{predictors}$ (without the time index to simplify the notation). The optimal combination, $\{s^*, p^*\}$, solves the following minimization problem:

$$\min_{s, p} \left\{ \min_{\overline{PAR}_1} \sum_{z_s \in R_1(s, p)} (PAR_y - \overline{PAR}_1)^2 + \min_{\overline{PAR}_2} \sum_{z_s \in R_2(s, p)} (PAR_y - \overline{PAR}_2)^2 \right\} \rightarrow \{s^*, p^*\}, \quad (3)$$

where the subindex y identifies realizations of the PAR that belong to a region, and $\overline{PAR}_k, k = 1, 2$ denote the region-specific means of the PAR .

While the resulting two regions already form a simple regression tree, we can obtain a finer partition of the predictor space by applying the search-and-split algorithm to both the left and the right top-level regions, which results in two second-level combinations of optimal splitting predictors and optimal splitting points, and four second-level region-specific means of the PAR . Upon recursively applying the search-and-split algorithm in

this way, we obtain an increasingly complex regression tree, which we can use to predict the *PAR*:

$$T(\mathbf{x}_i, \{R_l\}_1^L) = \sum_{l=1}^L \overline{PAR}_l \mathbf{1}(\mathbf{z}_i \in R_l), \quad (4)$$

where L = number of regions and $\mathbf{1}$ = indicator function.

It should be noted at this stage, as outlined in the introduction, that the search-and-splitting algorithm accounts in a purely data-driven way for: (i) a potential non-linearity in the link between the *PAR* and *CPU*; and, (ii) for potential interaction effects between *CPU* and the other predictors that we include in our empirical model (for a detailed discussion of the pros and cons of regression trees, see the textbook by Hastie et al. (2009)).

The complicated hierarchical structure of such a complex regression tree is likely lead to an overfitting and a data-sensitivity problem. Pruning a regression tree mitigates the overfitting problem, but it also most likely produces less precise forecasts. The idea motivating a random forest is that, rather than growing a pruned regression tree, the overfitting problem can be solved by growing an ensemble of regression trees in three steps:

1. Start by computing a large number of bootstrap samples by resampling from the data.
2. Grow a *random* regression tree on every bootstrap sample. To this end, apply the search-and-splitting algorithm to a random subset of the predictors and, thereby, mitigate the effect of influential predictors on tree building.
3. Combine the large number of random regression trees to a random forest. The prediction of the *PAR* is the average prediction obtained from the large number of individual random regression trees. Averaging stabilizes the resulting predictions.

We use the R language and environment for statistical computing (R Core Team 2023) and the R add-on package “randomForestSRC” (Ishwaran and Kogalur, 2023) to estimate random forests. We bootstrap with replacement and use 500 individual regression trees to grow a random forest (increasing the number of regression trees to 2,000 does not change our results in any substantive way). We fix the minimum node size at five and use a random of one third of the predictors for splitting, which is also the default value used in the package, so that our results are not shaped by the choice of non-standard hyperparameters. We refer a reader for details to the extensive documentation of the package.

4 Empirical Results

We begin our presentation of the results by presenting in Figure 2 a scatterplot of the *PAR* and *CPU*. In addition, we superimpose on this scatterplot the predicted values we obtain from a simple full-sample bivariate local weighted Gaussian regression of the *PAR* on *CPU*. The scatterplot along with the regression results show that movements of the *PAR* are hardly associated with climate policy uncertainty whenever the latter takes on relatively small values (approximately in general less slightly than 100). In the range between approximately slightly lower than 100 (which is around the median value of 88.6514 and mean value of 104.3461) and 200 of *CPU*, in contrast, we observe a marked negative association between the two variables, that is, an increase in *CPU* is accompanied by a decrease in the *PAR*. For large realizations of *CPU*, in turn, the regression line becomes essentially flat again. It follows that the link between the *PAR* and *CPU* is likely to be nonlinear and moderately negative.¹² In fact, the full-sample Pearson's product-moment correlation coefficient takes on the value -0.3255 and is strongly statistically significant, with a *t*-value of -7.2048.¹³

– Figure 2 about here. –

We next extend the regression model to include the various other measures of economic and policy related uncertainties, geopolitical risks, as well as controls defining the state of the macroeconomy and financial markets, as defined in the vector X_t in Equation 1. Including these additional predictors substantially inflates the number of variables, and so we estimate the extended regression model on the full sample of data by means of random forests. In doing so, we control in a data-driven way for potential interaction effects between the predictors. Importantly, we account for potential nonlinear links between the *PAR* and its drivers, including *CPU*, i.e., our primary predictor of interest. The partial-dependence function, which we plot in Figure 3, depicts the apparent nonlinear link between *PAR* and *CPU*. The partial-dependence function indicates that the *PAR* is stable when *CPU* takes

¹²These observations are also confirmed when we estimate a quantile-on-quantile regression model, in line with Sim and Zou (2015), whereby we find, as reported in Figure A1 at the end of the paper (Appendix), that the negative (nonlinear) effect at (especially the upper) quantiles of *PAR* strengthens beyond the median of *CPU*.

¹³Using the wavelet localized multiple correlation (WLMC) approach of Fernandez-Macho (2018), the negative association of *CPU* with *PAR* is, in general, confirmed not only over time, but also frequency-bands, particularly over to short- to medium-run as shown in Figure A2 (Appendix).

on comparatively small numerical values, but sharply decreases when *CPU* increases to intermediate values in the range of approximately 100 and 150. For values of *CPU* above this range, *PAR* stays constant at a lower level.

– Figure 3 about here. –

We summarize in Table 1 results for the relative importance of the various predictor variables for tree building.¹⁴ The lagged *PAR* is the single most important predictor, indicative of its persistence, followed by *FFR + SSR*, *GPRA*, and *CPU*. Hence, while the relative importance of *CPU* is moderate, on balance, it appears to be relatively more important than the various other measures of economic and policy related uncertainties, as well as the macroeconomic and financial indicators. This finding should not come as a surprise given that climate risks tend to carry predictive information for the state of the macroeconomy, conditions of financial markets, and even general economic uncertainties (Sheng et al. (2022a, 2022b), Bonato et al. (2023), Çepni et al. (2023), Del Fava et al. (forthcoming)). Naturally, uncertainty around non-specific climate policies to tackle global warming is likely to contain information on the conditions of the various economic sectors of the US.

– Table 1 about here. –

It is also interesting to trace out how the relative importance of *CPU* has evolved over time. To this end, we recursively estimate the random forests model. We use the first 10 years of data to initialize the estimations, and then recursively expand the window until we reach the end of the sample period. In Figure 4, we plot the resulting time-series of relative importance of *CPU*, as well as the rank of *CPU* among the various predictors according to its relative importance. The key and important message to take home from here is that the relative importance of *CPU* has grown at the end of the sample period, potentially reflecting the fact that attention to climate risks has grown substantially in recent years.¹⁵

– Figure 4 about here. –

¹⁴Due to the random nature of random forests, these numbers slightly change across different estimations of the model, but the overall picture remains the same.

¹⁵This observation is also in line with the findings of the (WLMC) method reported in Figure A2.

5 Concluding Remarks

Factors potentially affecting the US presidential approval ratings have received considerable interest in earlier research. Our empirical results, based on a machine-learning approach, demonstrate that climate policy uncertainty, a relatively new factor, deserves close scrutiny in the wake of the fact that attention to climate change and global warming has grown considerably in recent years in the media, in policy circles, and, last but not least, in the electorate. While we have found that the association of the presidential approval ratings with climate policy uncertainty is moderately negative and nonlinear in the monthly sample period of 1987:04-2023:12, we have found that climate policy uncertainty tends to be relatively more important than other measures of policy-related uncertainties, as well as many prominent macroeconomic and financial indicators used in earlier research. In addition, the importance of climate policy uncertainty appears to have grown in recent years in terms of its impact on the ratings of approval of the US president, in line with the growing concern of the impacts of global warming. In sum, our findings suggest that the influence of uncertainty associated with climate policies on public approval of the performance of the incumbent president in office can no longer be ignored, especially given that presidential approval ratings are likely to determine the chances of (re-)election. To put alternatively, clear-cut mandate involving policies on how to tackle climate change is likely to play an increasingly prominent role going forward in terms of determining outcomes of presidential elections, given that climate risks impacts the macroeconomy in general, as well as financial markets. In light of this finding, it is interesting, as part of future research and contingent on data availability, to extend our research to other developed and emerging countries.

References

- Baker, S.R., Bloom, N.A., and Davis, S.J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4), 1593–1636.
- Bonato, M., Cepni, O., Gupta, R., and Pierdzioch, C. (2023). Climate risks and state-level stock market realized volatility. *Journal of Financial Markets*, Volume 66(C), 100854.
- Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5–32.
- Breiman, L., Friedman, J.H., Oshen, R., and Stone, C. (1983). *Classification and regression trees*. New York: Chapman and Hall.
- Caldara, D., and Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, 112(4), 1194–1225.
- Çepni, O., Gupta, R., Liao, W., and Ma, J. (2023). Climate risks and forecastability of the weekly state-level economic conditions of the United States. *International Review of Finance*. DOI: <https://doi.org/10.1111/irfi.12431>.
- Chen, Z., Da, Z., Huang, D., and Wang, L. (2023). Presidential economic approval rating and the cross-section of stock returns. *Journal of Financial Economics*, 147(1), 106–131.
- Choi, S-W., James, P., Li, Y., and Olson, E. (2016). Presidential approval and macroeconomic conditions: evidence from a nonlinear model. *Applied Economics*, 48(47), 4558–4572.
- Del Fava, S., Gupta, R., Pierdzioch, C., and Rognone, L. (Forthcoming). Forecasting international financial stress: The role of climate risks. *Journal of International Financial Markets, Institutions and Money*.
- Fernandez-Macho, J. (2018). Time-localized wavelet multiple regression and correlation. *Physica A: Statistical Mechanics and its Applications*, 492(C), 1226–1238.
- Gavrilidis, K. (2021). Measuring climate policy uncertainty. Available at SSRN: <https://ssrn.com/abstract=3847388>.

- Giglio, S., Kelly, B., and Stroebe, J. (2021). Climate finance. *Annual Review of Financial Economics*, 13, 15–36.
- Gupta, R., Kanda, P.T., and Wohar, M.E. (2021). Predicting stock market movements in the United States: The role of presidential approval ratings. *International Review of Finance*, 21(1), 324–335.
- Gupta, R., Jaichand, Y., Pierdzioch, C., and van Eyden, R. (2023). Realized stock-market volatility of the United States and the presidential approval rating. *Mathematics*, 11(13), 2964.
- Hastie, T., Tibshirani, R., and Friedman J. (2009). *The elements of statistical learning. Data mining, inference, and prediction*, 2nd ed., Springer, New York.
- Ishwaran H., and Kogalur U.B. (2023). Fast unified random forests for survival, regression, and Classification (RF-SRC). R package version 3.2.2.
- R Core Team (2023). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. URL: <https://www.R-project.org/>.
- Sheng, X., Gupta, R., and Cepni, O. (2022a). Persistence of state-level uncertainty of the United States: The role of climate risks. *Economics Letters*, 215(C), 110500.
- Sim, N., and Zhou, A. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking and Finance*, 55(C), 1–8.
- Wu, J.C., and Xia, F.D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit, and Banking*, 48(2-3), 253–291.

Table 1: Relative variable importance (in percent)

Predictor	Relative importance
PAR_{t-1}	72.3160
FFR +SSR	6.4247
GPRA	5.4366
CPU	3.0980
NFCI	2.3713
Inflation	1.9238
National security	1.7833
GPRT	1.2398
Health care	0.9823
Government spending	0.9236
Monetary policy	0.6287
Trade policy	0.5451
Taxes	0.5359
Entitlement	0.4906
Financial regulation	0.4450
Regulation	0.3007
Sovereign debt and currency crisis	0.3524
Regulation	0.3007
CFNAI	0.2023

Figure 1: The data

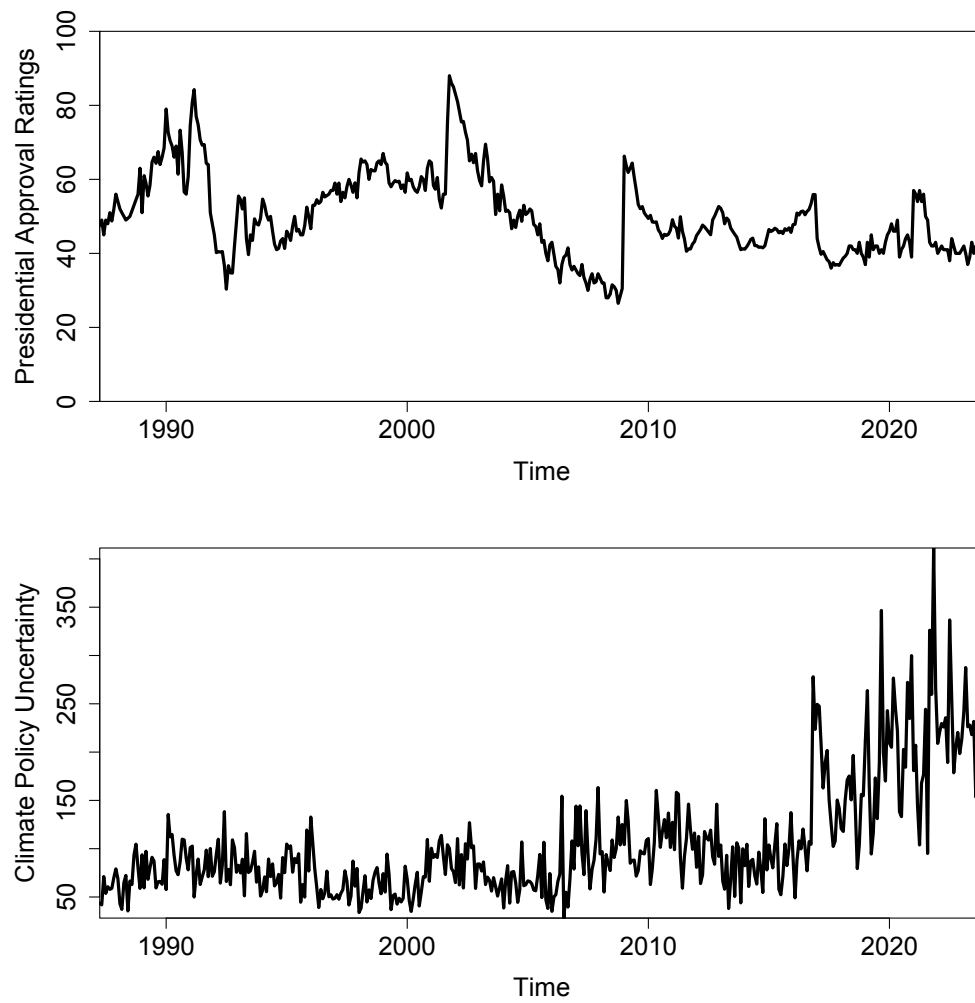
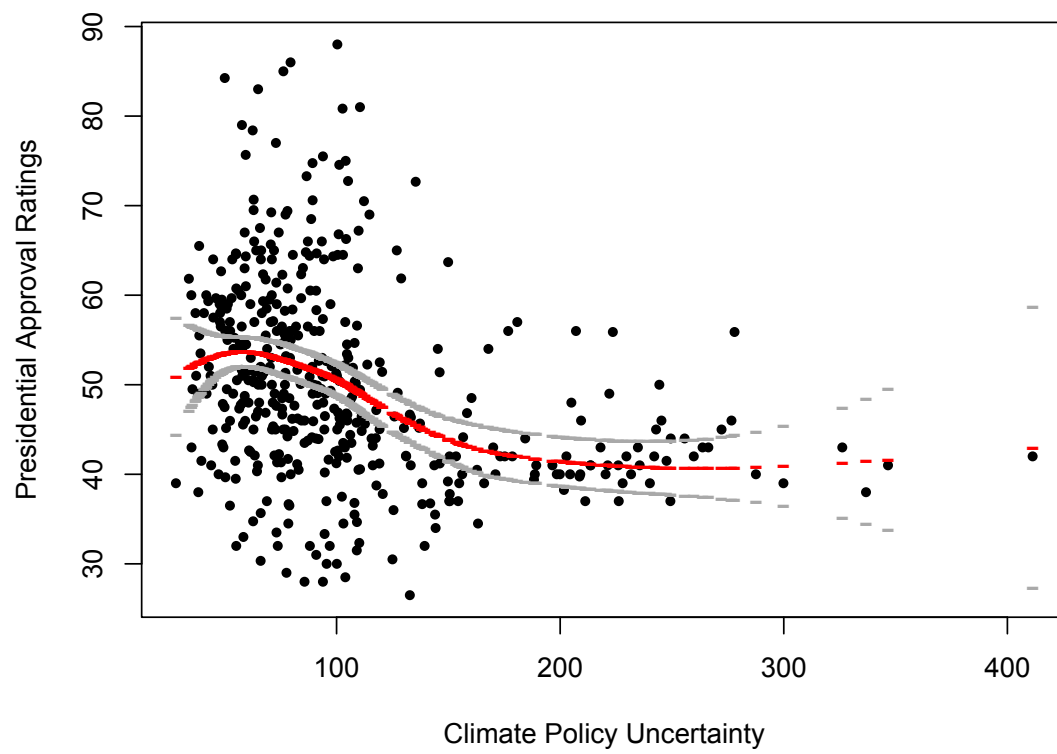


Figure 2: Local weighted Gaussian regression



The dashed lines denote $\pm 2 \times$ standard-error bands.

Figure 3: Partial-dependence function

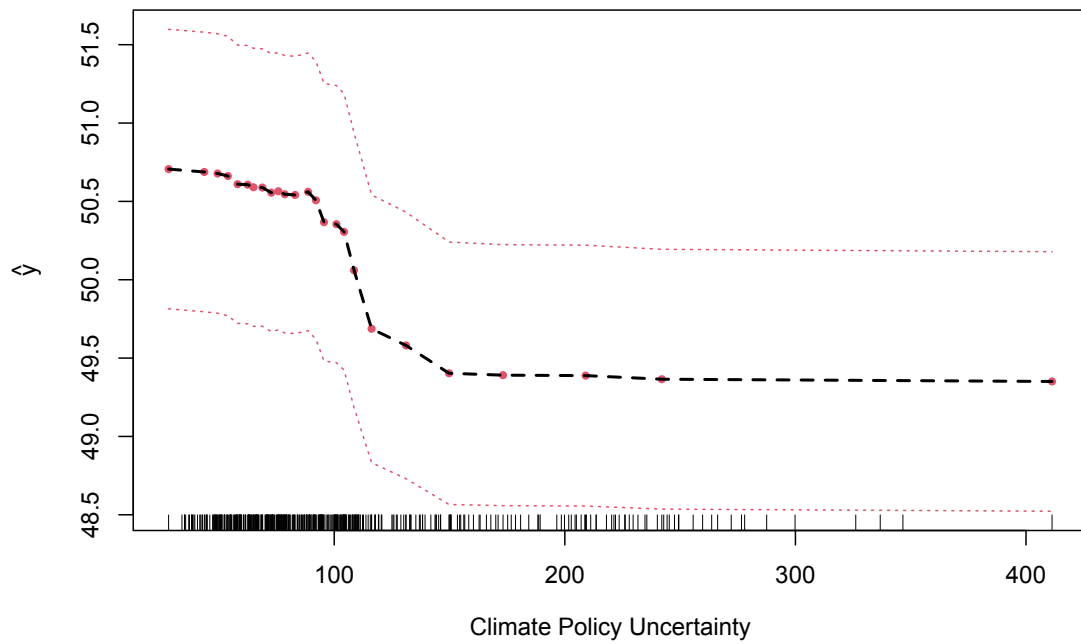
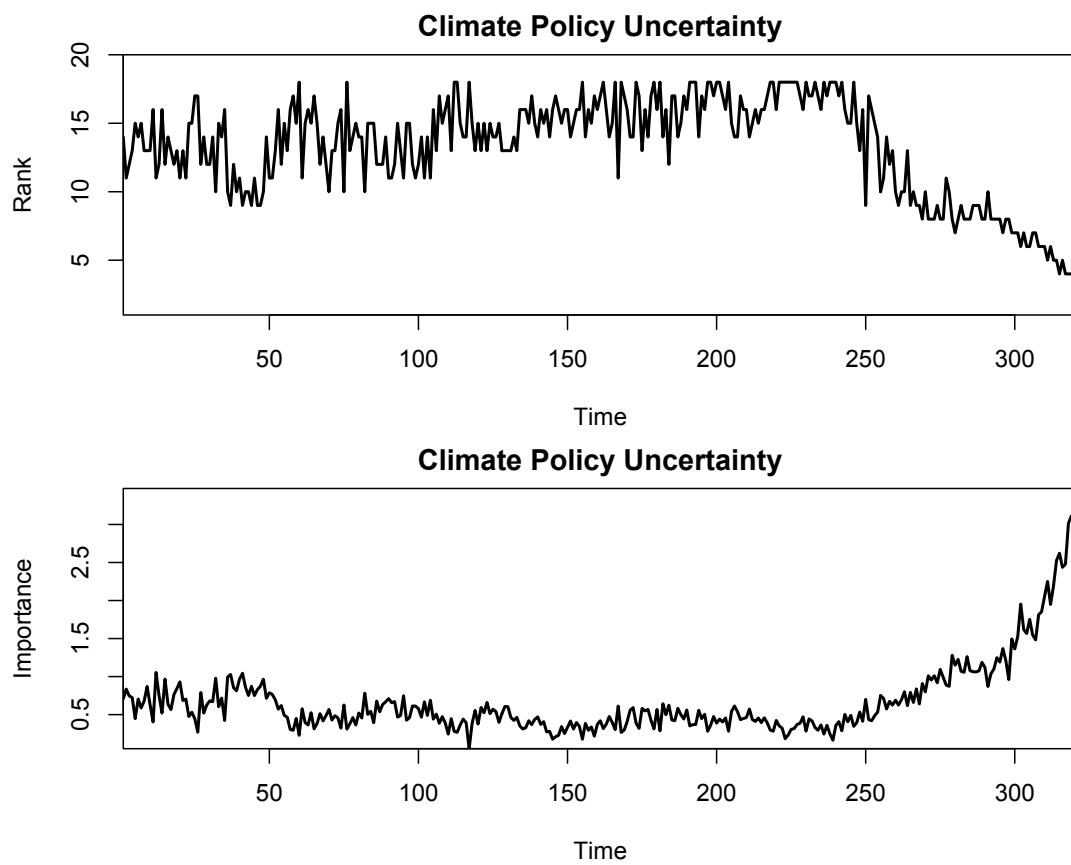


Figure 4: Recursive estimates of the relative importance



Appendix

Figure A1: Quantile-on-quantile regression

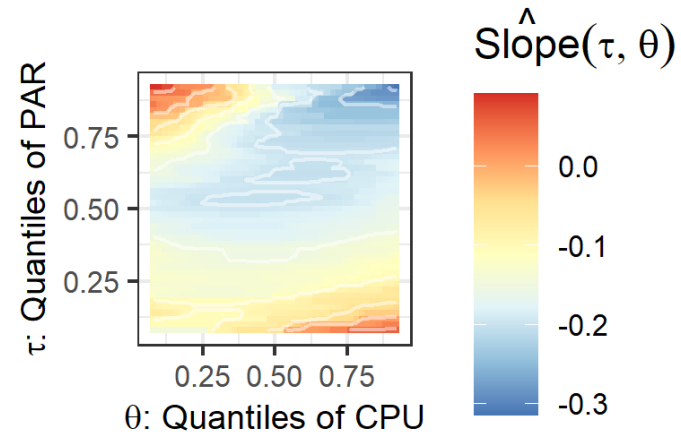


Figure A2: Wavelet localized multiple correlation

