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.

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1 Introduction

Climate change is certainly 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 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? The fact that this could indeed be an important issue in the presidential race is justified by the findings from a recently conducted (25th April to 4th May, 2024) nationally representative survey: Climate Change in the American Mind, conducted jointly by the Yale Program on Climate Change Communication and the George Mason University Center for Climate Change Communication. Based on interviews of 1031 adults of 18 years and above, 62% of registered voters indicated that they prefer "to vote for a candidate for public office who supports action on global warming...". In addition, 39% of registered voters pointed out that "a candidate's position on global warming will be "very important" when they decide who they will vote for in the 2024 presidential election".[2]

Intuitively, the link between climate policy uncertainty and presidential approval ratings could occur through both direct and indirect channels. Uncertainty regarding climate policy decisions is likely to raise transition risks associated with the adoption of "green technologies", and eventually may result in delays in the process of moderation of physical risks. This, in turn, could impact adversely the welfare of the citizens of a country in case extreme weather shocks become more frequent (Ma et al., 2023). Naturally, this would play

[1] See: https://globalcarbonatlas.org/emissions/carbon-emissions/, and also the discussion in Zhang et al. (2024).

[2] See: https://climatecommunication.yale.edu/wp-content/uploads/2024/06/climate-change-american-mind-politics-poli pdf, for complete details.

a direct role in shaping the perception of the population towards the role played by the US president in adopting clear-cut, i.e., less uncertain climate policies. At the same time, an indirect association could arise in case adverse effect of climate risks, which can serve as a metric of disaster events, inflate general uncertainty and, thereby, negatively affect the growth of the US economy (Sheng et al., forthcoming), with eventual recessionary outcomes again impacting the degree of support for the incumbent or new presidential candidate.

We address our question in hand 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; see also the survey by Berlemann and Enkelmann (2014)).[3] 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 are a fully data-driven approach that can accurately trace out the link between presidential approval ratings and a large number of its drivers, automatically accounting for the admissible range of realizations of the presidential approval ratings. In addition, the results of estimating random forests can be easily summarized by means of partial-dependence functions and measures of relative predictor importance, which makes it straightforward to interpret estimation results in economic and political terms. Moreover, the idea behind random forests as well as their basic structure are easy to understand even in case a reader is not familiar with statistical-learning techniques. Importantly, random forests automatically capture potential nonlinear links between the US presidential approval ratings and climate policy uncertainty, controlling for interactions of the latter with 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 our empirical results show, a nonlinear link of US presidential approval ratings is strongly

[3]While 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.

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.[4] 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 Gavriilidis (2021), who focuses on scaled frequency, i.e., percentage, of climate policy-related articles to total number of articles from eight leading US newspapers[5] that include the terms "uncertainty" or "uncertain" and "carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO_2" 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".[6]

The categorical data involving policy related uncertainties consists of a range of sub-indexes of Baker at al.'s (2016) overall economic policy uncertainty (EPU) index, based

[4]The data is publicly available for download from: http://www.presidency.ucsb.edu/data/popularity.php.

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

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

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.[7]

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).[8] 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 newspapers[9] 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,

[7]The 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`.

[8]The data can be downloaded from: `https://www.matteoiacoviello.com/gpr.htm`.

[9]Chicago 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.[10] In this regard, we also utilize the year-on-year consumer price index (CPI)-based inflation rate ($Inflation$), and stance of monetary policy ($FFR + SSR$) as captured by the Federal Funds Rate (FFR) merged with the Shadow Short Rate (SSR) of Wu and Xia (2016), with the latter capturing unconventional monetary policy decisions when the FFR reaches its zero lower bound.[11] 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.[12]

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

[10] The data is freely available at: https://www.chicagofed.org/research/data/cfnai/current-data.

[11] The CPI and FFR data are obtained from the FRED databse maintained by the St. Louis Fed, while the SSR is downloadable from: https://sites.google.com/view/jingcynthiawu/shadow-rates?authuser=0.

[12] The 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:

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

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:

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

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 = predictors (without the time index to simplify the notation). The optimal combination, $\{s^*, p^*\}$, solves the following minimization problem:

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

where the subindes 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:

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

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.[13] 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.[14]

– 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

[13]These 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.

[14]Using the wavelet localized multiple correlation (WLMC) approach of Fernández-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.[15]

– Figure 3 about here. –

We summarize in Table 1 results for the relative importance of the various predictor variables for tree building.[16] 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 (Ding et al. (2022), Sheng et al. (2022a, 2022b), Bonato et al. (2023), Çepni et al. (2023), Ren et al. (2023), Sun et al. (2023), Del Fava et al. (2024)). 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.[17] 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

[15]Reasonable changes of the parameters of the random-forest model (like increasing the number of trees, sampling without replacement, or changing the number of splitting variables gives qualitatively similar partial-dependence function. Complete details are available from the authors upon reasonable request.

[16]Due to the random nature of random forests, these numbers slightly change across different estimations of the model, but the overall picture remains the same. Again, reasonable changes of the parameters of the random-forest model give similar results (available from the authors upon request). We scaled the numbers we report in Table 1 so that they add up to 100% (up to the usual rounding error).

[17]We plot at the end of the paper (Figure A3) results for a rolling-estimation window of length 10 years. The results for a rolling-estimation window exhibit, as expected, a somewhat larger variability than those for a recursive-estimation window, but corroborate the results for the latter in that a general trend towards a greater relative importance of climate-policy uncertainty can be observed.

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.[18]

– Figure 4 about here. –

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 influence the chances of (re-)election. To put alternatively, a 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 are likely to impact the macroeconomy in general, as well as financial markets.

In light of our findings, it is interesting, as part of future research and contingent on data availability, to extend our research to other developed and emerging countries. Currently, our results are only limited to the US, but to obtain a general conclusion regarding the nexus between uncertainties surrounding climate policy and possibility of reelection of

[18] This observation is also in line with the findings of the (WLMC) method, reported in Figure A2.

political parties and candidates, it is indeed important to extend our econometric exercise to a wider panel of heterogeneous economies.[19] In addition, because in-sample association does not guarantee accurate out-of-sample predictions (Campbell, 2008), future research can also be conducted in this context from the perspective of a forecasting experiment. Finally, given that behavior of climate risks across US states tend to be heterogeneous (Gil-Alana et al., 2022), ideally one would like to look at state-specific measures of climate policy uncertainty in this context.[20]

[19] In this regard, what might also be appealing would be to look at how international cooperation in combating climate change plays a role, as outlined in Dai (2023) involving China and the US. In fact, using a simple linear regression, we found that the measure of US climate policy uncertainty tends to increase (with a coefficient value of 0.9785) in a statistically significant manner (at the 1% level) if there is a rise in a newspapers-based metric of China-US tension, developed recently by Rogers et al. (2024). The index is available for download from: `https://sites.google.com/site/bosun09/u-s-china-tension?authuser=0` (and starts in January, 1993).

[20] As part of preliminary analysis, given that climate policy uncertainty is not available for the US states at this stage, we conducted standard linear Granger causality test running from state-level measures of overall economic policy uncertainty, developed by Baker et al. (2022) using newspapers articles, on the US presidential approval ratings. The data can be downloaded from: `https://policyuncertainty.com/state_epu.html`, and covers three indexes for each state in a non-uniform manner starting in 1985:01: EPU_National (i.e., state uncertainty due to national policies), EPU_State (i.e., state uncertainty due to state and local policies), and composite of the former two, i.e., EPU_Composite. In general, the causal influence is found to be weak: Illinois (10% level), Indiana (5% level), Kentucky (5% level), Michigan (5% level), Minnesota (10% level), Missouri (5% level), Montana (10% level), Texas (1% level), Washington (5% level), and Wyoming (10% level) under EPU_National; Hawaii (5% level), Montana (1% level), Tennessee (10% level), Texas (10% level) and Wyoming (10% level) due from EPU_State, and; from EPU_Composite of Indiana (5% level), Kentucky (5% level), Montana (1% level), New Hampshire (10% level), South Carolina (5% level) and Texas (1% level). This observation is possibly an indication of the need to resort to a nonlinear model for such an exercise.

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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

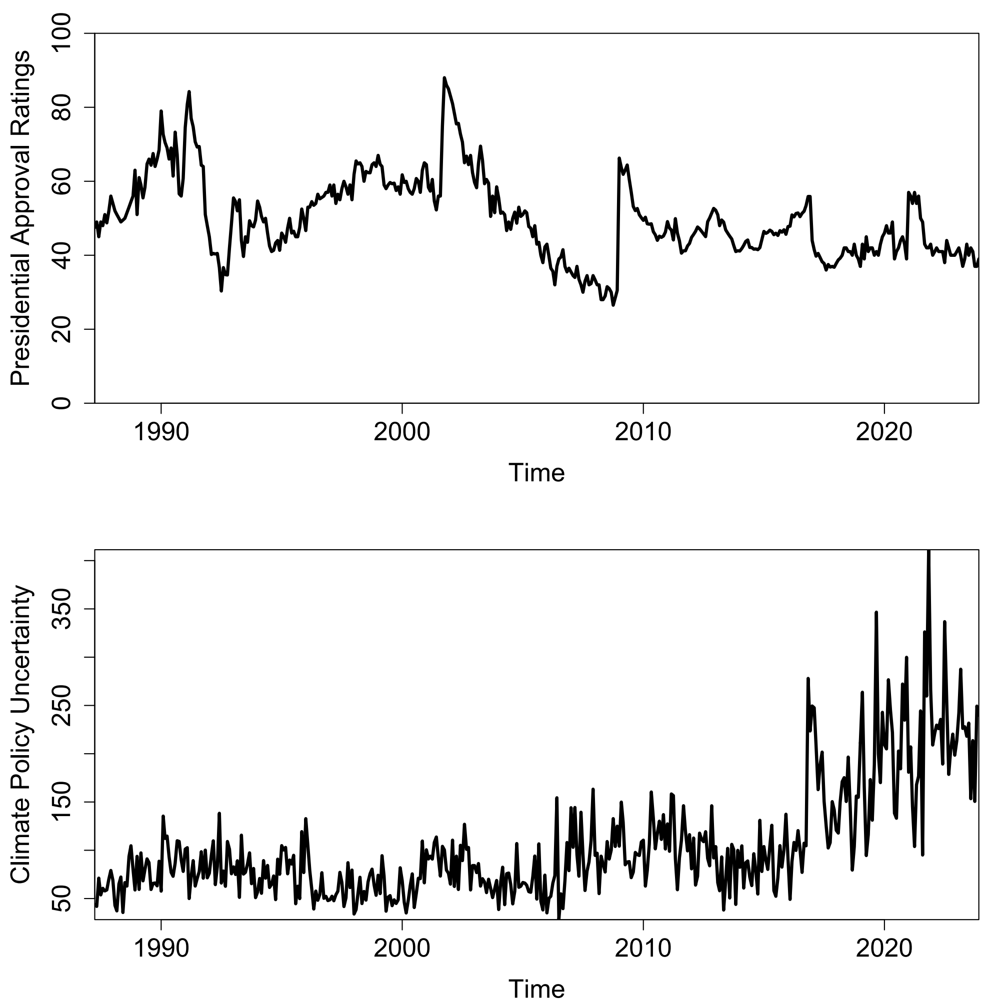
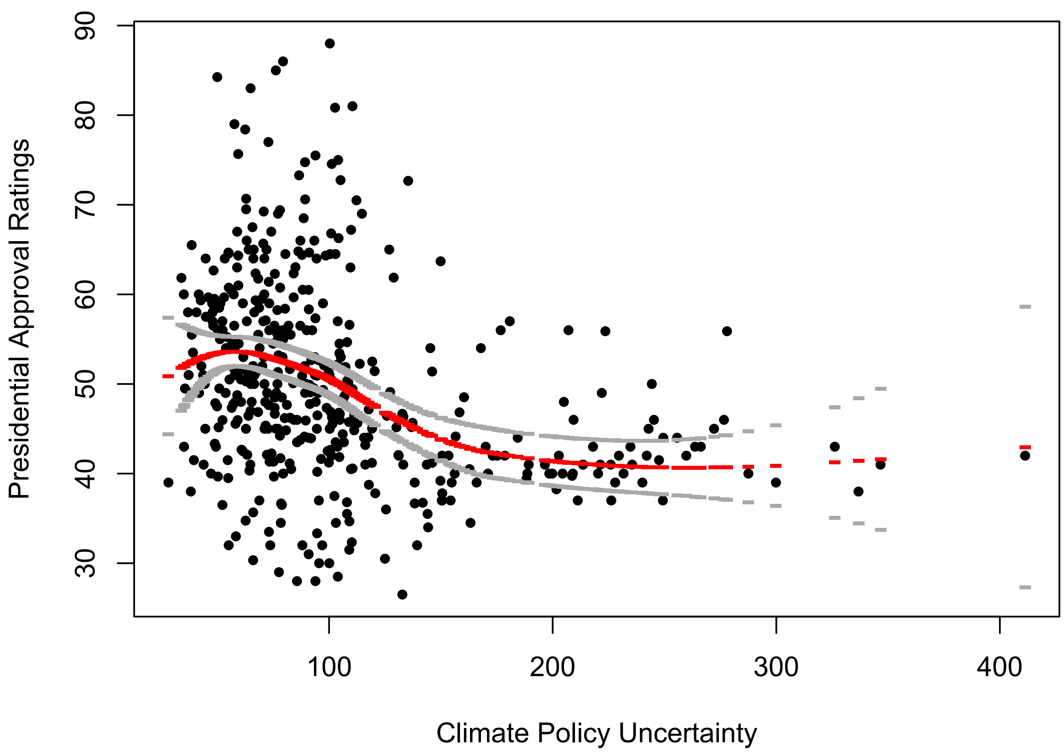


Figure 2: Local weighted Gaussian regression



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

Figure 3: Partial-dependence function

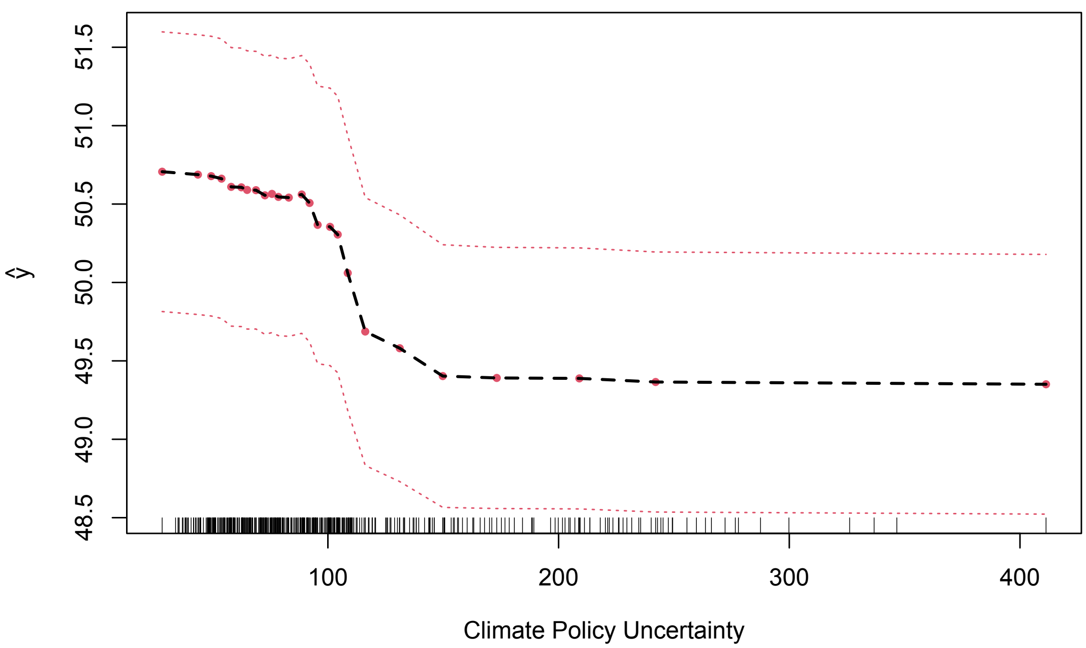
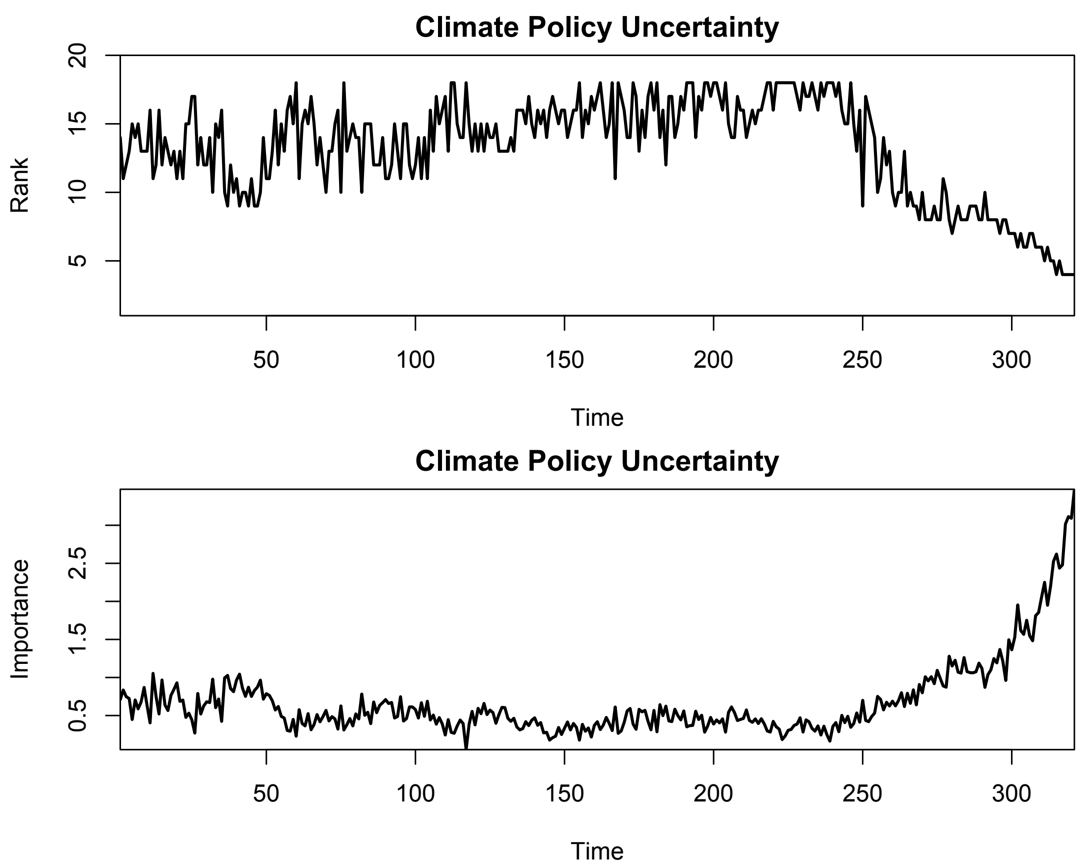


Figure 4: Recursive estimates of relative importance



Appendix

Figure A1: Quantile-on-quantile regression

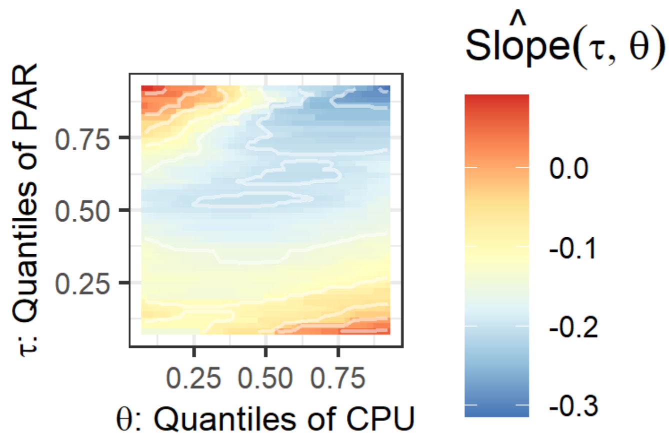


Figure A2: Wavelet localized multiple correlation

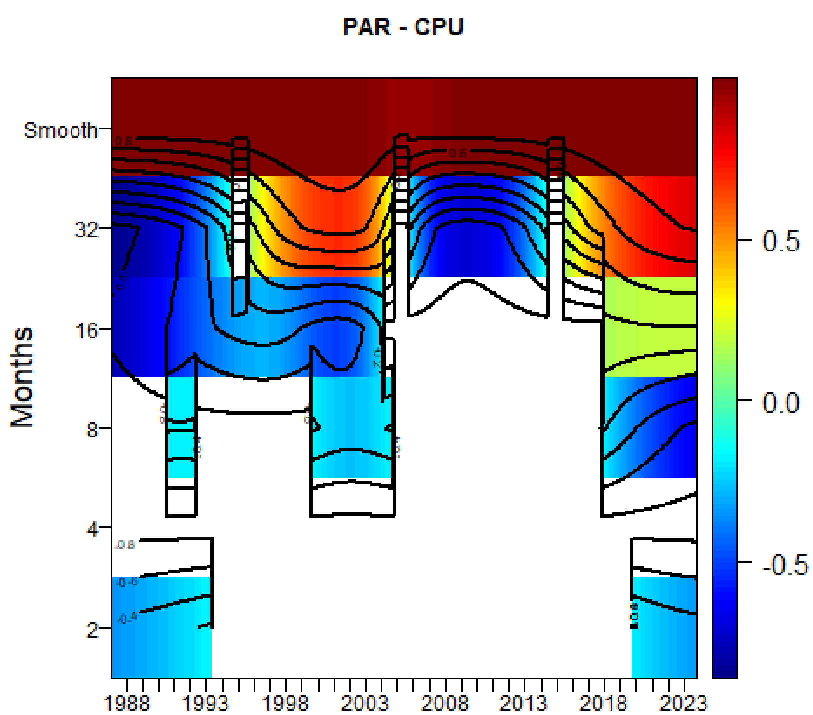


Figure A3: Rolling estimates of relative importance