

Min(d)ing the President:

A text analytic approach to measuring tax news

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ONLINE APPENDIX

Appendix A Additional results for the prevalence and tax news measures

A.1 Results about predictability

In Tables A.1-A.8 we investigate the predictive ability of the tax prevalence measures for a variety of tax change measures by means of F -tests and R^2 statistics. We regress various measures of tax changes on the tax topics and a set of control variables. More specifically, we estimate the following predictive regressions

$$\Delta T_t = \gamma_0 + \gamma'_1 \mathbf{z}_{t-j} + \sum_{i=1}^{12} \beta'_i \mathbf{x}_{t-i} + u_t \quad \text{for } j = 0, 1, 2, \dots, 6, \quad (\text{A.1})$$

where ΔT_t is a tax change series, $\mathbf{z}_t$ contains tax topic prevalence measures, and $\mathbf{x}_t$ contains control variables. γ_0 is an intercept. We estimate (A.1) for several endogenous tax change series. Controls always include lags of the dependent variable, first differences of log GDP and first differences of log government spending, as well as interest rates.¹ The strength of the correlation between the tax topics contained in $\mathbf{z}_{t-j}$ and ΔT_t j quarters ahead can be assessed by comparing the (marginal) F -statistic to their χ_p^2/p critical values, with the

¹Our analysis is build on time series sampled at quarterly frequency from 1949Q1-2007Q4. Details about the economic data used in this paper can be found in Appendix C.2.

degrees of freedom p equal to the number of variables in $\mathbf{z}_t$.² As measures of tax changes we consider changes in (cyclically adjusted) tax receipts and two of RR’s narrative measures of tax changes.³

Table A.1 reveals that the prevalence measure obtained from the first-stage unsupervised LDA (i.e. the general tax topic) is not a powerful predictor for any tax change measure considered. This finding serves as a note of caution against a too confident use of unsupervised text analytics. Table A.5 shows the (marginal) F -statistic on the (joint) exclusion of the tax cut and tax hike topics from various predictive regressions. Regardless of how we measure future tax changes, the F -statistic is, for several forecast horizons, well above the cut-off for any reasonable significance level.

The above conclusions are also supported when considering the predictive power of the various measures in terms of change in R^2 . Table A.2 shows that the general tax topic from first-stage LDA offers little improvement over the controls in predicting the measures of tax changes. The tax cut and tax hike topics obtained from the second-stage LDA jointly offer far greater improvement in predictive power across all measures of tax changes, as seen in Table A.6. Additionally, Tables A.3 and A.4 suggest that those topics tend to be stronger predictors than analogous measures constructed using a simple lexicon-based approach.

One may also use the same predictive regressions and F -statistics for testing whether these measures can be used as strong instruments of the regressand using the procedure laid out in Stock and Yogo (2005). Comparing to the rule of thumb cut-off point of 10 (Staiger and Stock, 1997), but also to the stricter critical values tabled in Stock and Yogo (2005) that guarantee small size distortion,⁴

²At 95%, these values are equal to 3.84 and 3.00 for $p = 1$ and $p = 2$, respectively.

³RR link tax changes directly to the legislative process and, thus, their narrative contains more precise information about the timing of tax changes. We consider RR’s series quantifying expected changes in current tax liabilities at time of implementation (i.e. for the first fiscal year the law was scheduled to be in effect) and the associated discounted present value at time of enactment. The latter measure is interpreted by RR as a signal containing tax news (in the strict sense of providing (almost) perfect foresight, i.e. there is no uncertainty of whether the tax change will happen or not). Further, RR construct sub-components of those measures capturing “exogenous” tax changes only (i.e. changes not driven by recent economic conditions). All narratives taken from RR are expressed as ratio to nominal GDP.

⁴As argued by Stock and Yogo (2005), while the cut-off of 10 is reasonable to control bias, for having low size distortion we need to consider larger cut-off points. To control size distortion at maximum 5% (10%), the 95% critical values are 16.38 (8.96) and 19.93 (11.59) for 1 and 2 instruments respectively. We see that the F -statistics for the second-stage tax topics regularly exceed the cut-offs, unlike the first stage tax topic or the lexicon-based series,

One may argue that, due to their construction, our prevalence series may pick up news signals about other policy plans that would affect the federal budget in the future, notably government spending. However, as indicated in the last rows of Tables A.5 and A.6, our measures do not possess much power in predicting federal spending (news).⁵

For comparison, we additionally summarise F -tests and changes in R^2 indicating the predictive strength of the implicit tax rates from Leeper et al. (2012) (see Tables A.7 and A.8).

Finally, In Figure A.1 we report the results of the Granger causality tests of Hecq et al. (2023) described in Section III.C.

As mentioned in Section IV.B, we investigate next the contemporaneous relationship between our tax prevalence measures and other identified topics. Figure A.2 displays estimates of the correlation coefficient as well as 95% confidence intervals. In particular, we find that the topic related to regulatory policies (*Public Administration*) as well as the one we associate with policies aiming at improving long-run economic conditions (*Economic Development*) correlate significantly with the the two tax prevalence measures.

and we may therefore reject the null hypothesis that the second-stage tax topics are weak instruments. This suggests that the second-stage tax topics series can not only be considered strong predictors of future tax changes, but could also be used as strong instruments for tax changes.

⁵Overall, the above findings are robust across different specifications of the regression in (A.1). Unreported results, considering other control variables such as the party of the sitting president, election year, etc., do not alter the results.

Table A.1: F -statistics on the exclusion of the prevalence measure obtained from the first-stage unsupervised LDA.

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	F_{max}
Tax change measures:									
Change in aggregate tax receipts	0.03	0.00	0.11	0.30	0.63	0.04	0.31	4	0.63
Change in cycl. adj. revenue	0.06	2.44	3.40	2.10	3.18	0.00	2.90	2	3.4
R&R (2010) – Expected change in tax liabilities at time of implementation	0.73	5.38	1.59	1.04	0.83	0.58	6.37	6	6.37
R&R (2010) – Expected change in tax liabilities at time of enactment	11.31	1.57	0.33	2.19	0.07	0.4	0.27	0	11.31
Spending change measures:									
Change in government consumption expenditures	1.73	0.00	3.60	1.30	3.38	0.01	0.13	2	3.6
Ramey’s (2011) spending news	0.11	0.66	0.18	1.17	0.65	0.12	0.03	3	1.17

Table A.2: Percentage point change in R^2 from including tax topic prevalence measures obtained from the first-stage unsupervised LDA.

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	ΔR^2_{max}
Tax change measures:									
Change in aggregate tax receipts	0.01	0	0.04	0.1	0.2	0.01	0.1	4	0.2
Change in cycl. adj. revenue	0.02	0.83	1.16	0.71	1.07	0	0.98	2	1.16
R&R (2010) – Expected change in tax liabilities at time of implementation	0.23	1.67	0.5	0.32	0.25	0.18	1.9	6	1.9
R&R (2010) – Expected change in tax liabilities at time of enactment	2.99	0.43	0.09	0.6	0.02	0.11	0.08	0	2.99
Spending change measures:									
Change in government consumption expenditures	0.54	0	1.18	0.43	1.11	0	0.04	2	1.18
Ramey’s (2011) spending news	0.04	0.23	0.06	0.4	0.23	0.04	0.01	3	0.4

Table A.3: F -statistics on the joint exclusion of the tax cut and tax hike topics from a simple Lexicon approach.

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	F_{max}
Tax change measures:									
Change in aggregate tax receipts	1.31	4.57	2.17	0.93	4.91	1.59	4.64	4	4.91
Change in cycl. adj. revenue	0.39	5.24	2.07	0.63	6.98	2.14	6.08	4	6.98
R&R (2010) – Expected change in tax liabilities at time of implementation	0.35	5.05	5.08	3.13	4.72	4.13	2.43	2	5.08
R&R (2010) – Expected change in tax liabilities at time of enactment	12.37	7.35	4.88	3.73	2.92	0.48	1.14	0	12.37
Spending change measures:									
Change in government consumption expenditures	1.18	0.88	6.24	3.23	3.86	1.27	2.55	2	6.24
Ramey’s (2011) spending news	0.28	0.29	0.67	1.74	2.03	0.71	0.06	4	2.03

Table A.4: Percentage point change in R^2 from jointly including the tax cut and tax hike topics from a simple Lexicon approach.

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	ΔR_{max}^2
Tax change measures:									
Change in aggregate tax receipts	1.09	5.94	6.7	10.7	3.9	3.51	0.45	3	10.7
Change in cycl. adj. revenue	0.06	4.05	6.83	7.26	4.22	4.7	1.97	3	7.26
R&R (2010) – Expected change in tax liabilities at time of implementation	1.1	2.72	5.54	8.91	10.07	6.71	7.18	4	10.07
R&R (2010) – Expected change in tax liabilities at time of enactment	6.07	3.65	11.57	7.44	6.58	0.41	1.7	2	11.57
Spending change measures:									
Change in government consumption expenditures	1.41	0.61	1.43	0.36	0.65	0.83	0.56	2	1.43
Ramey’s (2011) spending news	0.27	0.56	0.5	0.37	0.38	0.03	0.01	1	0.56

Table A.5: F -statistics on the joint exclusion of the tax cut and tax hike topics from the second-stage semi-supervised LDA.

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	F_{max}
Tax change measures:									
Change in aggregate tax receipts	1.76	10.25	11.65	19.87	6.48	5.77	0.70	3	19.87
Change in cycl. adj. revenue	0.09	6.20	10.87	11.85	6.56	7.34	2.95	3	11.85
R&R (2010) – Expected change in tax liabilities at time of implementation	1.76	4.44	9.56	16.76	19.23	12.05	13.09	4	19.23
R&R (2010) – Expected change in tax liabilities at time of enactment	12.11	6.96	25.5	15.23	13.24	0.73	3.11	2	25.5
Spending change measures:									
Change in government consumption expenditures	2.27	0.93	2.20	0.55	0.99	1.24	0.82	0	2.27
Ramey's (2011) spending news	0.38	0.80	0.73	0.54	0.54	0.04	0.01	1	0.8

Table A.6: Percentage point change in R^2 from jointly including the tax cut and tax hike topics from the second-stage semi-supervised LDA.

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	ΔR^2_{max}
Tax change measures:									
Change in aggregate tax receipts	0.82	2.78	1.35	0.58	2.99	1	2.86	4	2.99
Change in cycl. adj. revenue	0.27	3.44	1.4	0.42	4.47	1.43	3.96	4	4.47
R&R (2010) – Expected change in tax liabilities at time of implementation	0.22	3.07	3.06	1.86	2.79	2.46	1.46	1	3.07
R&R (2010) – Expected change in tax liabilities at time of enactment	6.19	3.84	2.61	2.01	1.59	0.27	0.63	0	6.19
Spending change measures:									
Change in government consumption expenditures	0.74	0.58	3.92	2.08	2.49	0.85	1.73	2	3.92
Ramey’s (2011) spending news	0.2	0.2	0.45	1.18	1.39	0.5	0.04	4	1.39

Table A.7: F -statistics on the exclusion of implicit tax rates from Leeper et al. (2012).

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	F_{max}
Tax change measures:									
Change in aggregate tax receipts	2.15	3.62	0.06	0.27	0.57	0.34	0.17	1	3.62
Change in cycl. adj. revenue	0.42	2.50	0.27	0.75	0.28	0.44	0.01	1	2.50
R&R (2010) – Expected change in tax liabilities at time of implementation	1.51	0.36	0.81	0.05	1.57	2.69	3.80	6	3.80
R&R (2010) – Expected change in tax liabilities at time of enactment	0.64	0.64	0.28	1.49	0.07	0.71	1.43	3	1.49
Spending change measures:									
Change in government consumption expenditures	0.05	0.06	0.00	0.59	0.66	1.68	0.32	5	1.68
Ramey’s (2011) spending news	2.39	0.55	1.74	1.43	0.08	0.34	1.42	0	2.39

Table A.8: Percentage point change in R^2 from including implicit tax rates from Leeper et al. (2012).

Forecast Horizon	0	1	2	3	4	5	6	H_{max}	ΔR^2_{max}
Tax change measures:									
Change in aggregate tax receipts	0.73	1.23	0.02	0.09	0.2	0.12	0.06	1	1.23
Change in cycl. adj. revenue	0.15	0.91	0.1	0.28	0.1	0.16	0	1	0.91
R&R (2010) – Expected change in tax liabilities at time of implementation	0.49	0.12	0.27	0.02	0.52	0.89	1.25	6	1.25
R&R (2010) – Expected change in tax liabilities at time of enactment	0.19	0.19	0.08	0.45	0.02	0.22	0.43	3	0.45
Spending change measures:									
Change in government consumption expenditures	0.02	0.02	0	0.23	0.26	0.67	0.13	5	0.67
Ramey’s (2011) spending news	0.88	0.21	0.65	0.54	0.03	0.13	0.54	0	0.88

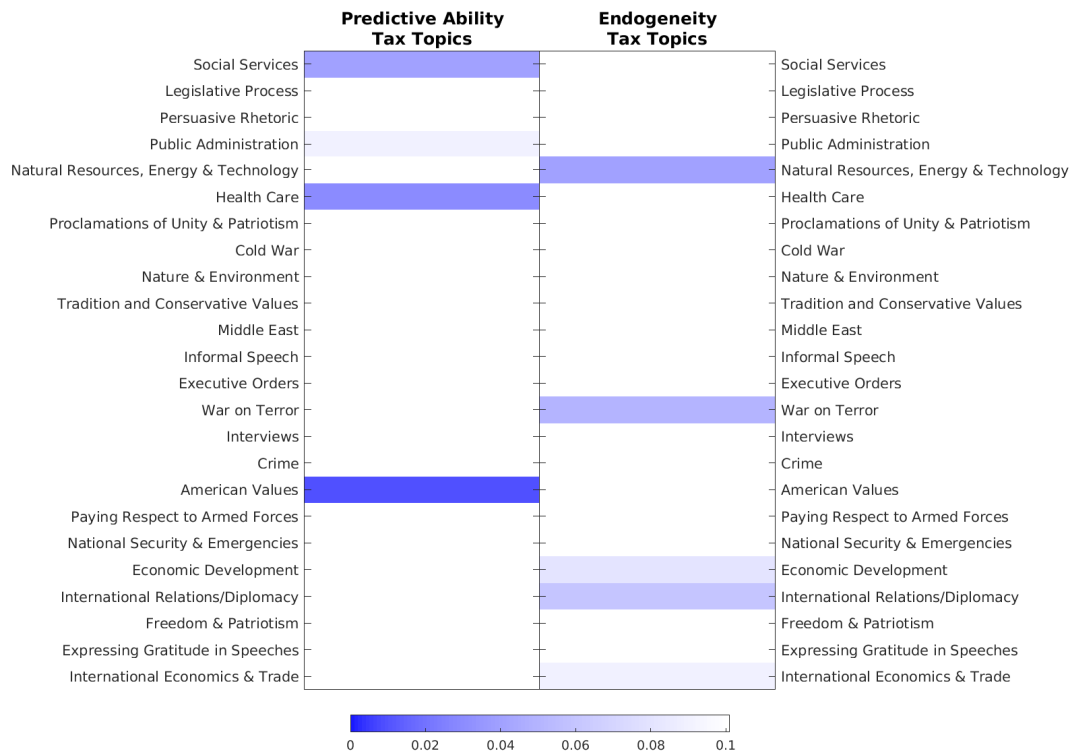


Figure A.1: p -Values from Granger causality tests. The left column (*Predictive Ability*) visualises to what extent the two tax prevalence measures jointly Granger-cause other identified topics. The right column (*Endogeneity*) depicts the extent to which the tax prevalence measures are Granger-caused by other identified topics.

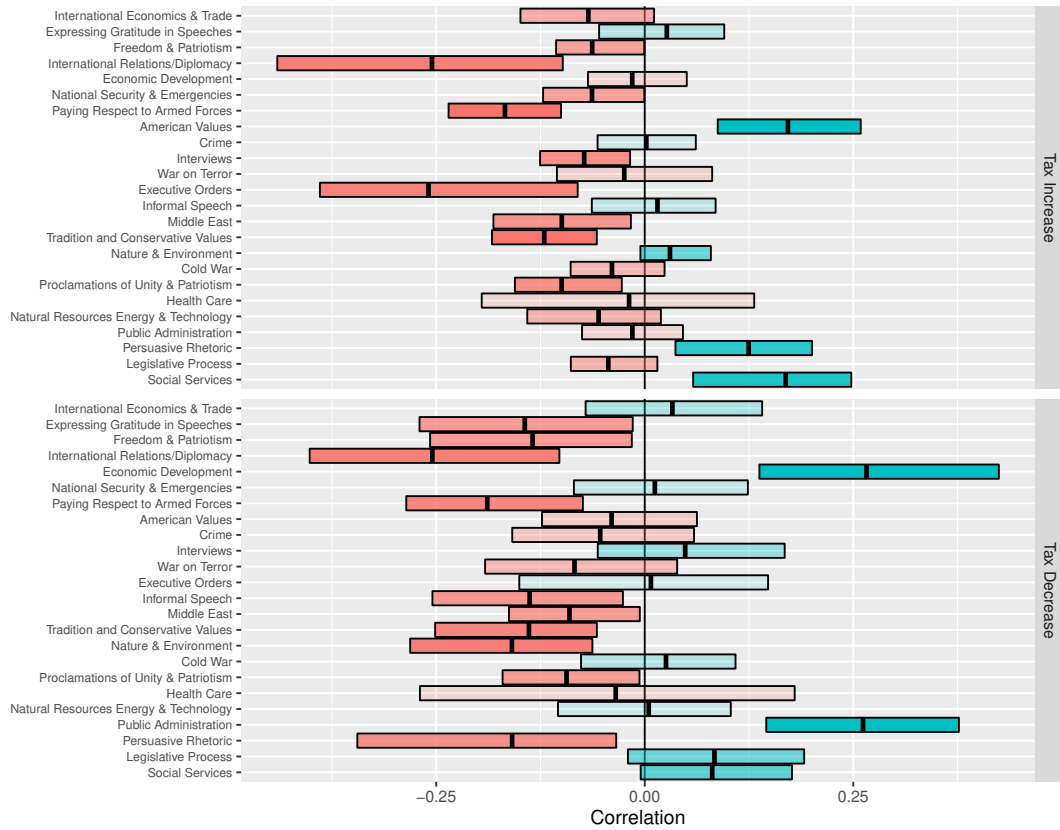


Figure A.2: Point estimates as well as 95% confidence intervals of the correlation coefficient between each of the tax prevalence measures (cuts and hikes) and other identified topics.

A.2 Effects of tax news for various model specifications

In this section we further investigate the robustness of the results presented in Section IV.B. We start with checking the effect of modifying the set of controls in the LP-IV regression. Figures A.3 and A.4 show impulse responses of output and tax receipts to news about a future tax cut for a short(er) and long(er) anticipation horizon, respectively, and for different sets of control variables. Apart from different regressors the model specification corresponds to the benchmark model discussed in Section IV.B (i.e. trends, lags, etc.). Responses of both variables don't differ much across the three different sets of controls considered, neither for short(er) nor for long(er) term anticipation. However, and in particular for $M = 1$ and $N = 4$, it is interesting to note that including in addition past (RR) tax changes (i.e. extending the set of regressors in Figures A.3(e) resp. A.3(f) by past tax changes) leads to a stronger post-implementation response of output, and to a weaker pre-implementation contraction. In contrast, the response of tax receipts is largely unaffected. This is possibly suggesting that tax changes with long phase-ins have indeed less strong expansionary effects on economic activity.

We next turn to the question whether the specification of the anticipation horizon, i.e. the choice of M and N affects the results. Investigating Figure A.5 leads to two conclusions. First, (i) the larger M , the larger the contractionary pre-implementation effect on output and the later the (trough) response in tax receipts. That is, the more we “force” the tax prevalence measures to instrument tax news relating to policy changes farther in the future, the stronger the (negative) anticipation effect on output. Second, comparing now responses across the rows in Figure A.5, (ii) the length of the “aggregation window” ($N - M$) does not alter the results as drastically. One can only observe a slightly lagged and more persistent response in both variables.

Figure A.6 complements Figure 7 in the text. That is a variety of changes in the model specification are investigated for the case of a short(er) anticipation horizon ($M = 1$ and $N = 4$). As can be seen from Figure A.6 no modification leads to a significantly different output response. Only changing the trend specification, that is considering only a linear trend, instead of a linear and quadratic trend, has a dampening effect on the response of GDP.

Next, we investigate how our approach of constructing tax news complements and compares to existing narrative approaches. With this aim, we analyse impulse responses of output and tax receipts to a change in $x_{1,t}$, which is constructed as in (3) using RR's exogenous tax changes as a measure for ΔT_t . Since we do not instrument $x_{1,t}$ with the tax prevalence measures, estimation is done by OLS using the benchmark specification of the local projection

regression discussed in Section IV.B. To make results comparable, the same normalization of impulse responses is applied. Results are displayed in Figure A.7. For soon-to-be implemented tax changes output responses are (qualitatively) similar for both tax news measures. However, when constructed using RR's narrative, news about a tax cut implemented in the more distant future does not lead to initial contractionary effects. Output does not react before tax changes are implemented. This suggests that RR's (exogenous) tax change series – if not further decomposed as in Mertens and Ravn (2012) – does not contain enough information to clearly identify anticipation effects.

Finally, we take a first step in analyzing whether tax cuts more effectively impact GDP compared to tax hikes. To investigate this we use the empirical framework as outlined in Section IV.A, however, we use our tax cut prevalence measure (and not our tax hike measure) to instrument tax cuts (thus only negative tax changes) in the RR series. We estimate responses to news about a tax hike similarly. The results in Figure A.8 suggest that regardless of the anticipation horizon, tax cuts have a stronger effect on output than tax hikes. We want to emphasise however, that we don't interpret these results as conclusive evidence of non-linear effects of tax changes - a much more careful investigation would be needed. Rather, we see these initial findings as motivation to possibly analyse this question more carefully in future research.

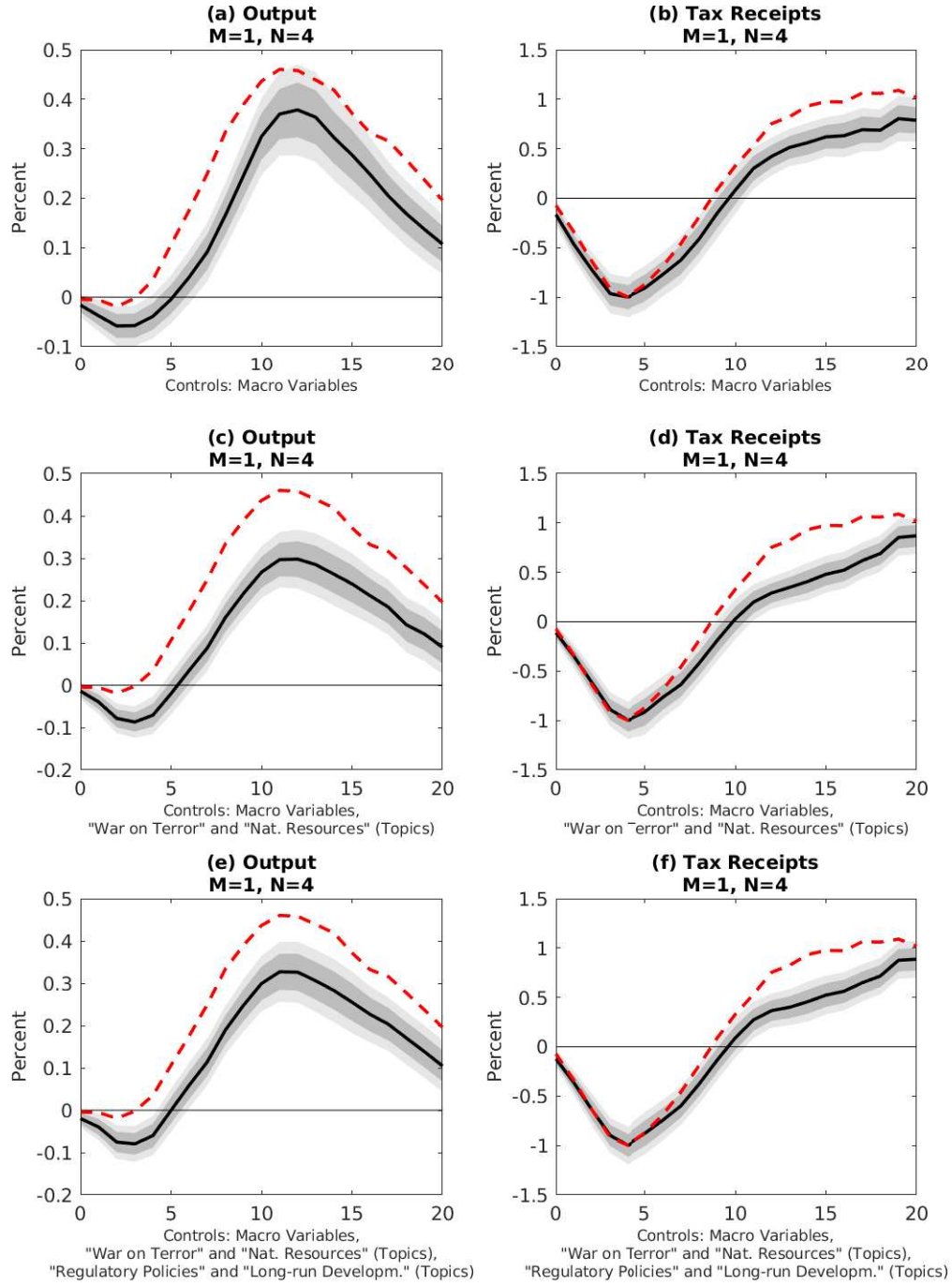


Figure A.3: Output and government revenue responses to news about a future tax cut with a short(er) anticipation horizon ($M = 1$ and $N = 4$) for various sets of control variables. Displayed are impulse responses (solid black lines) as well as 68% and 90% confidence intervals (gray shaded area). For comparison, impulse responses based on our benchmark set of regressors (cf. Figure 6) are also plotted (red dashed lines).

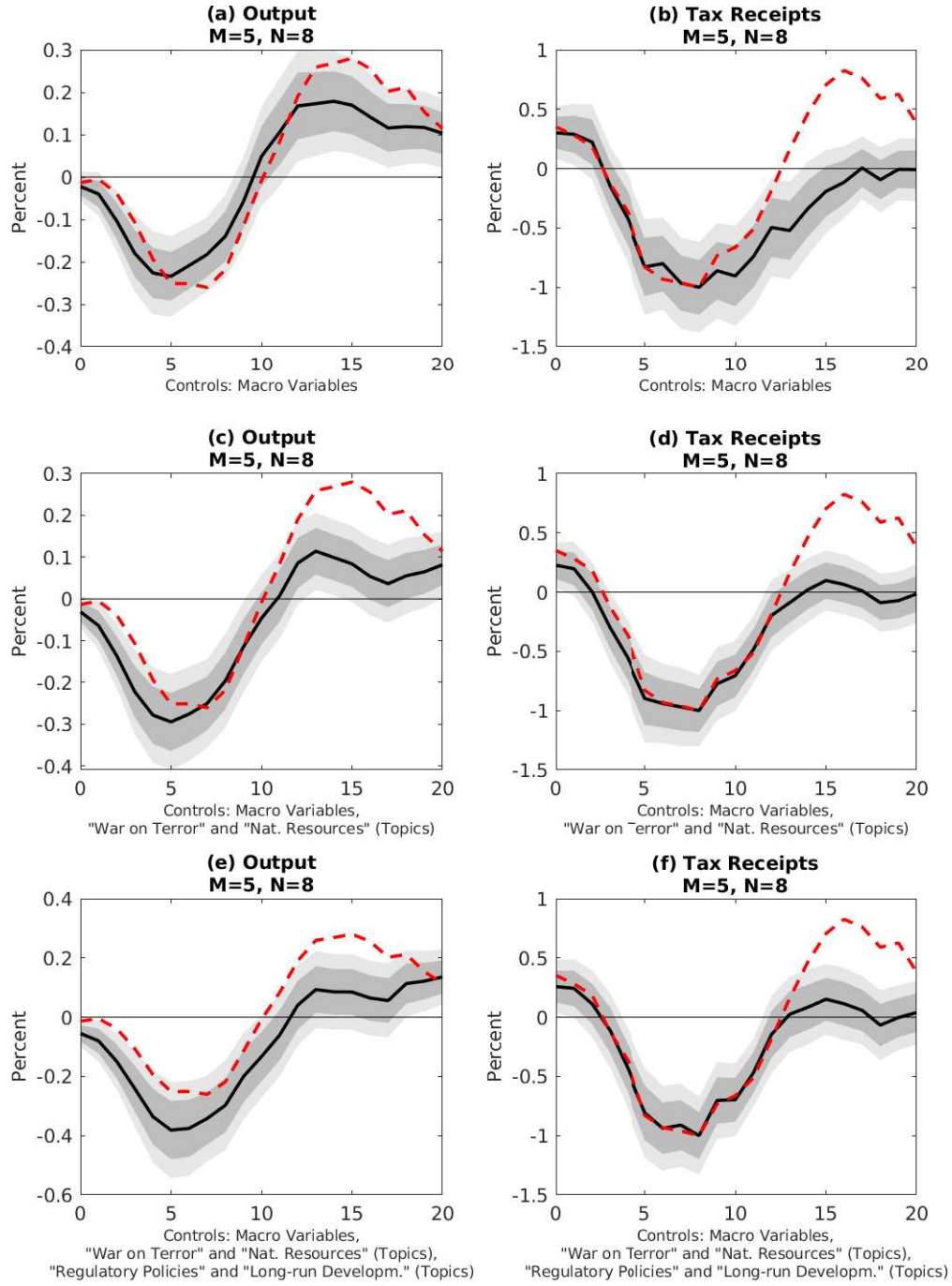


Figure A.4: Output and government revenue responses to news about a future tax cut with a long(er) anticipation horizon ($M = 5$ and $N = 4$) for various sets of control variables. Displayed are impulse responses (solid black lines) as well as 68% and 90% confidence intervals (gray shaded area). For comparison, impulse responses based on our benchmark set of regressors (cf. Figure 6) are also plotted (red dashed lines).

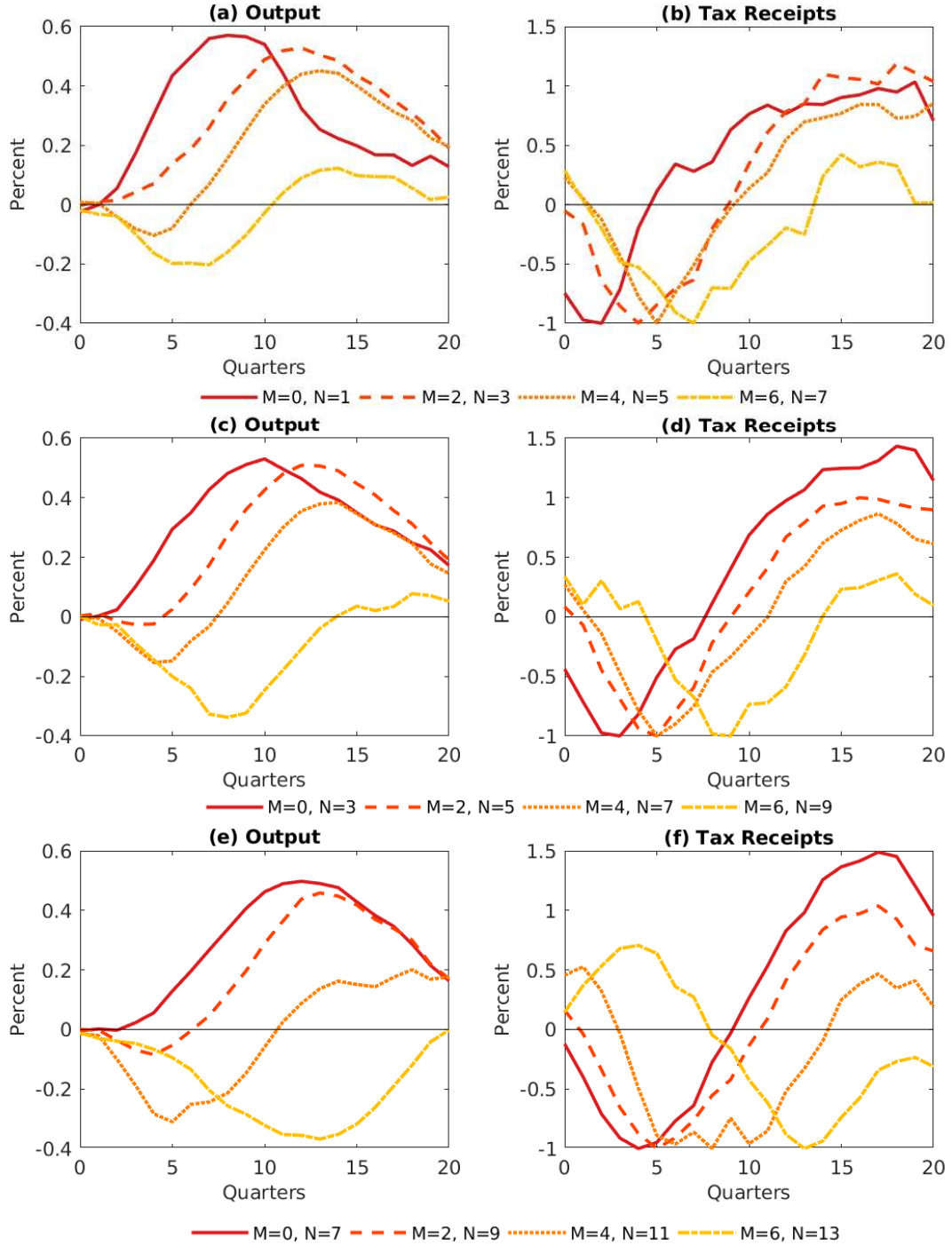


Figure A.5: Sensitivity of responses to varying anticipation horizon. Apart from different values of M and N the model specification (deterministic components, regressors, lags) correspond to the benchmark model discussed in Section IV.B.

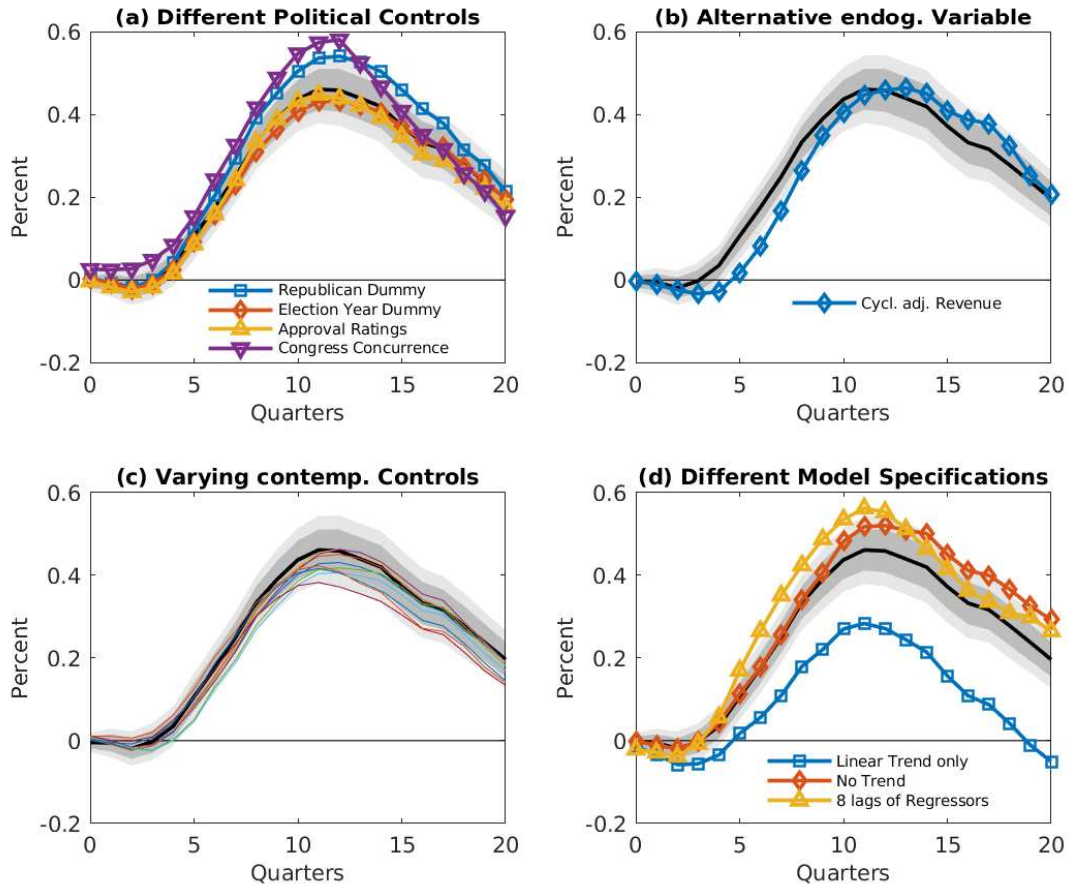


Figure A.6: Short(er) anticipation horizon (i.e. $M = 1$ and $N = 4$.)

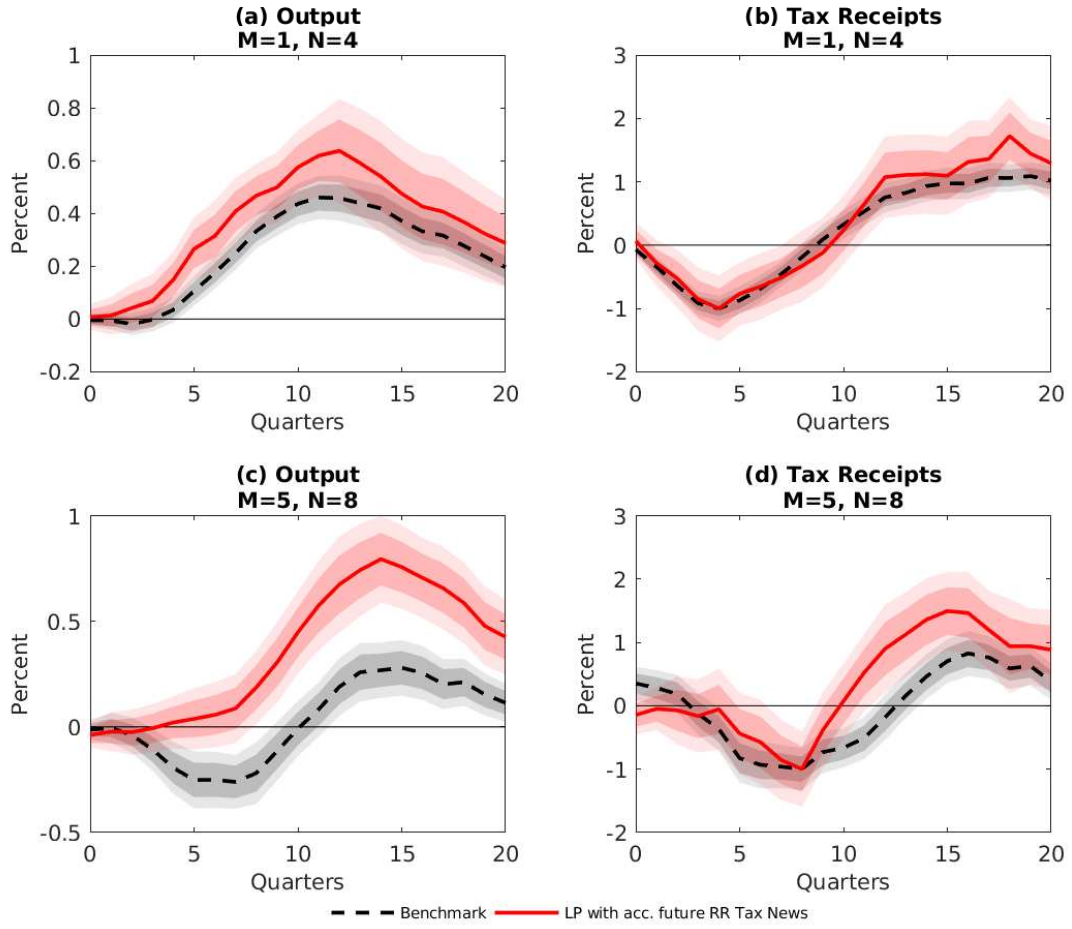


Figure A.7: Impulse responses estimated using local projections and a measure of future tax changes as constructed in (3) as shock variable of interest. The measure of future tax changes is constructed from RR's exogenous tax changes.

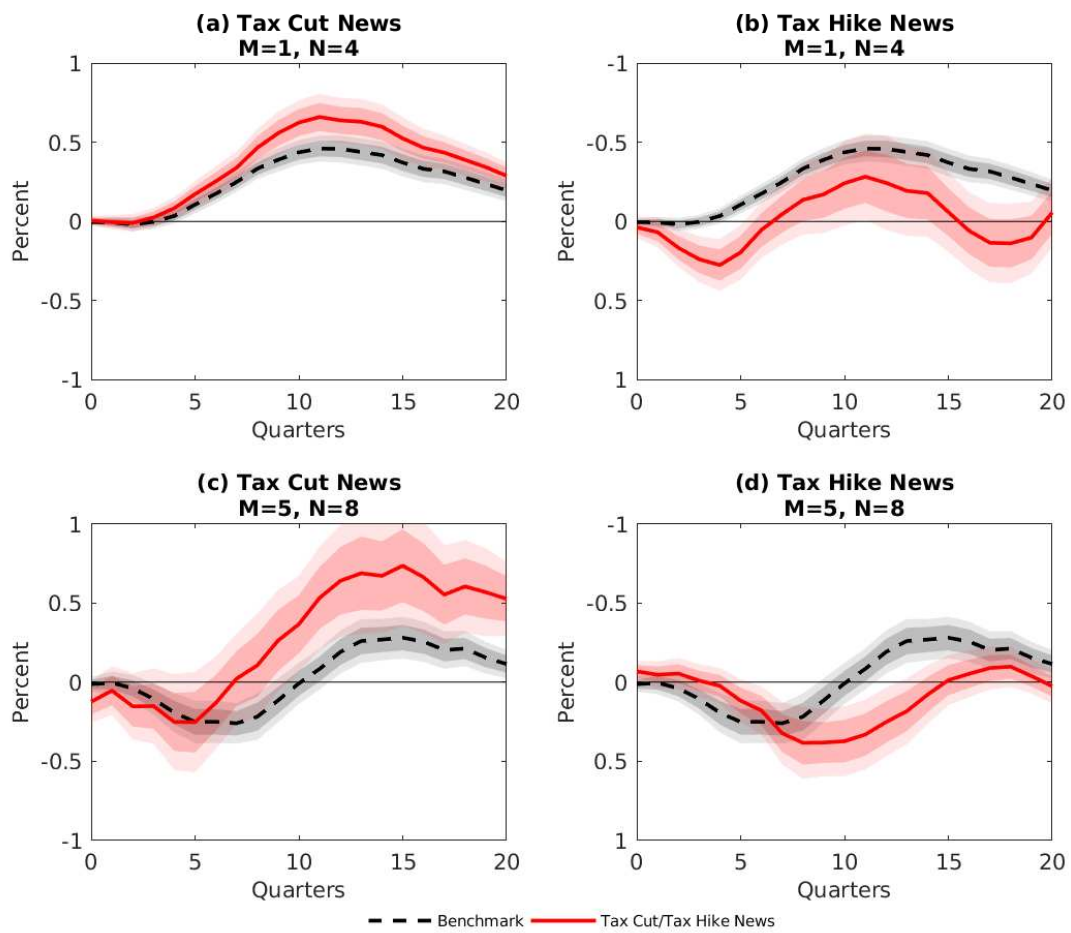


Figure A.8: Output responses to news about future tax cuts and to news about future tax hikes, respectively. For comparison, impulse responses based on the benchmark specification are plotted as well.

Appendix B Details for the two-step LDA model

B.1 Dirichlet distribution

A K -dimensional Dirichlet distribution is a continuous probability distribution, where a draw from the distribution is a vector of K non-negative numbers summing up to 1. For $\boldsymbol{\theta} \sim \text{Dir}(\boldsymbol{\alpha})$ the parameter vector $\boldsymbol{\alpha} = a\boldsymbol{\mu}$ is decomposed into two parts - a scalar concentration parameter $a = \sum_{k=1}^K \alpha_k$ and the mean vector $\boldsymbol{\mu} = \mathbb{E}[\boldsymbol{\theta}] = \frac{1}{a}\boldsymbol{\alpha}$. The higher the a the more concentrated the draws will be around the mean, following $\text{Var}[\theta_k] = \frac{\mu_k(1-\mu_k)}{a+1}$. This is visualised in Figure B.1.

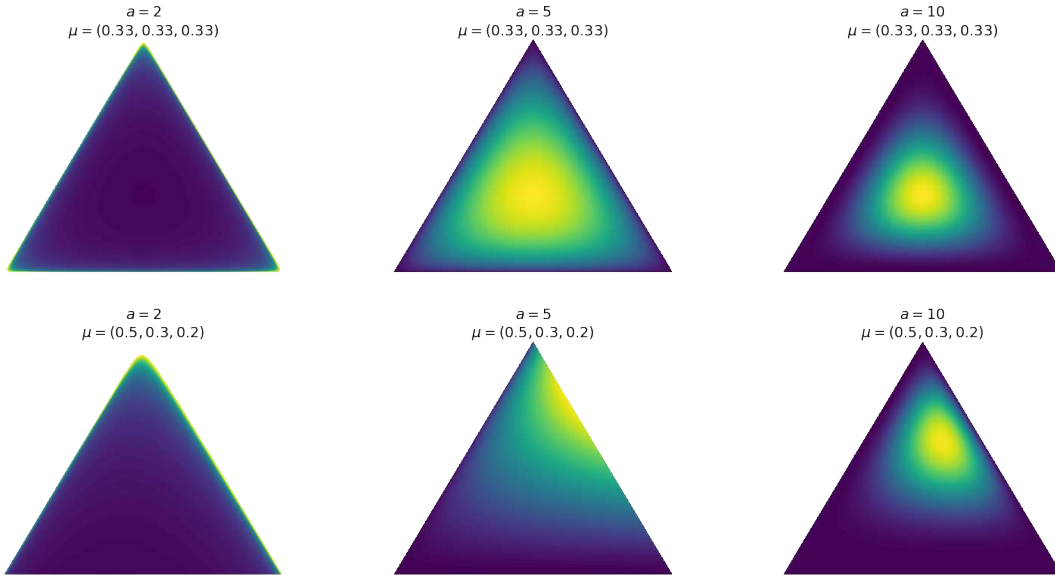


Figure B.1: Probability density graphs for $K = 3$ -dimensional Dirichlet distributions with mean $\boldsymbol{\mu}$ and concentration parameter a . The lighter the colour, the higher the density.

A specific advantage of the Dirichlet distribution for estimating LDA models is the conjugacy property of this distribution in Bayesian inference. As an example, consider a 3-topic model with $\theta_d \sim \text{Dir}(2, 1, 0.5)$. If based on the data we believe that the document d contains 0 tokens assigned to topic 1, 10 tokens assigned to topic 2 and 5 tokens assigned to topic 3, the posterior distribution for its mixing proportions is given by $\text{Dir}(0 + 2, 10 + 1, 5 + 0.5)$. Intuitively, the parameter vector for the prior can then be interpreted as a count vector of past observations, where we can influence the relative importance of terms through $\boldsymbol{\mu}$, and the weight of prior information through a .

The use of Dirichlet priors leads to the LDA's tendency to concentrate big

part of the probability mass of the mixing proportions in a relatively small number of topics, and big part of the probability mass of the topics' distributions in a relatively small number of terms. This behavior can be best seen when considering the distribution over the topic assignment $z_{d,n}$ for some token $w_{d,n}$, conditional on the topic assignments for the rest of the corpus $\mathcal{W}^{-d,n}, \mathcal{Z}^{-d,n}$:

$$\mathbb{P}(z_{d,n} = k | w_{d,n} = v_i, \mathcal{W}^{-d,n}, \mathcal{Z}^{-d,n}) \propto \underbrace{(N_d^{(k)} + \alpha_k)}_{\text{document}} \underbrace{\frac{N^{(k,i)} + \eta_{k,i}}{\sum_{d=1}^D N_d^{(k)} + \sum_{j=1}^V \eta_{k,j}}}_{\text{topic}},$$

where $N_d^{(k)} = \sum_{n=1}^{N_d} \mathbb{1}(z_{d,n} = k)$ is the number of tokens assigned to topic k in document d and $N^{(k,i)} = \sum_{d=1}^D \sum_{n=1}^{N_d} \mathbb{1}(w_{d,n} = v_i) \mathbb{1}(z_{d,n} = k)$ is the number of tokens with the term v_i assigned to topic k . This probability consists of two parts:

- In the document part, the more tokens within a document are identified as coming from topic k , the higher is $N_d^{(k)}$ and the higher the likelihood that the next token is also identified as coming from topic k .
- In the topic part, the more times the given term v_i is identified as coming from topic k (across the whole corpus), the higher $N^{(k,i)}$ and the higher the likelihood that the next instance of that term is also identified as coming from topic k .

B.2 Model specification

Our approach requires that the following parameters are specified. In the first, unsupervised step the number of topics K is 25; the shape and scale parameters (c, s) for the Gamma priors of the elements of $\boldsymbol{\eta}$ and $\boldsymbol{\alpha}$ are chosen to be 100^{-1} and 100 respectively. In the second step we split the *tax* topic into *tax increase* and *tax decrease* topic, resulting in $K = 26$; the parameters (c, s) for the Gamma priors of the elements of $\boldsymbol{\alpha}$ remain at 100^{-1} and 100 respectively, while the vectors $\boldsymbol{\eta}_k$, $k = 1, \dots, K$ are constructed according to (2).

In the first step the model consists of the following elements:

$$\eta_{k,i} = \eta, \quad \eta \sim \text{Gamma}(c, s) \quad p(\eta) = \frac{1}{\Gamma(s)c^s} \eta^{s-1} e^{-\frac{\eta}{c}} \quad (\text{B.1})$$

$$\phi_k | \boldsymbol{\eta}_k \sim \text{Dir}(\boldsymbol{\eta}_k) \quad p(\phi_k | \boldsymbol{\eta}_k) = \frac{\Gamma\left(\sum_{i=1}^V \eta_{k,i}\right)}{\prod_{i=1}^V \Gamma(\eta_{k,i})} \prod_{i=1}^V \phi_{k,i}^{\eta_{k,i}-1} \quad (\text{B.2})$$

$$\alpha_k \sim \text{Gamma}(c, s) \quad p(\alpha_k) = \frac{1}{\Gamma(s)c^s} \alpha_k^{s-1} e^{-\frac{\alpha_k}{c}} \quad (\text{B.3})$$

$$\boldsymbol{\theta}_d | \boldsymbol{\alpha} \sim \text{Dir}(\boldsymbol{\alpha}) \quad p(\boldsymbol{\theta}_d | \boldsymbol{\alpha}) = \frac{\Gamma\left(\sum_{k=1}^K \alpha_k\right)}{\prod_{k=1}^K \Gamma(\alpha_k)} \prod_{k=1}^K \theta_{d,k}^{\alpha_k-1} \quad (\text{B.4})$$

$$\begin{aligned} z_{d,n} | \boldsymbol{\theta}_d &\sim \text{Cat}(\boldsymbol{\theta}_d) & \mathbb{P}(z_{d,n} = k | \boldsymbol{\theta}_d) &= \theta_{d,k} \\ w_{d,n} | z_{d,n} = k, \boldsymbol{\Phi} &\sim \text{Cat}(\boldsymbol{\phi}_k) & \mathbb{P}(w_{d,n} = v_i | z_{d,n} = k) &= \phi_{k,i} \end{aligned}$$

In the second step, instead of estimating $\boldsymbol{\eta}_k$, $k = 1, \dots, K$ according to (B.1) we construct them according to (2) and treat them as known.

B.3 Estimation of the topic model

Here we describe the Bayesian estimation procedure to obtain the posterior distribution of the document mixing proportions $\boldsymbol{\Theta}$ and topics' term probabilities $\boldsymbol{\Phi}$, conditional on the observed corpus of documents $\mathcal{W}$ and the Dirichlet distribution parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\eta}_k$'s.

The complete data likelihood of the LDA model is

$$p(\mathcal{W}, \mathcal{Z} | \boldsymbol{\Theta}, \boldsymbol{\Phi}) = \prod_{d=1}^D \prod_{n=1}^{N_d} \prod_{i=1}^V \prod_{k=1}^K (\theta_{d,k} \phi_{k,i})^{\mathbb{1}(z_{d,n}=k) \mathbb{1}(w_{d,n}=v_i)}. \quad (\text{B.5})$$

The posterior of the model is obtained by combining the likelihood in (B.5)

and the priors in (B.2) and (B.4):

$$\begin{aligned}
& p(\Theta, \Phi, \alpha, \eta_1, \dots, \eta_K, \mathcal{Z} | \mathcal{W}) \\
& \propto p(\mathcal{W}, \mathcal{Z} | \Theta, \Phi) p(\Theta | \alpha) p(\Phi | \eta_1, \dots, \eta_K) p(\alpha) p(\eta_1, \dots, \eta_K) \\
& \propto \left(\frac{\Gamma(\sum_{k=1}^K \alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k)} \right)^D \prod_{k=1}^K \left(\frac{\Gamma(\sum_{i=1}^V \eta_{k,i})}{\prod_{i=1}^V \Gamma(\eta_{k,i})} \right) p(\alpha) p(\eta_1, \dots, \eta_K) \\
& \quad \times \prod_{d=1}^D \prod_{k=1}^K \theta_{d,k}^{\alpha_k - 1 + \sum_{i=1}^V \sum_{n=1}^{N_d} \mathbb{1}(z_{d,n}=k) \mathbb{1}(w_{d,n}=v_i)} \\
& \quad \times \prod_{k=1}^K \prod_{i=1}^V \phi_{k,i}^{\eta_{k,i} - 1 + \sum_{d=1}^D \sum_{n=1}^{N_d} \mathbb{1}(z_{d,n}=k) \mathbb{1}(w_{d,n}=v_i)}.
\end{aligned}$$

Posterior inference of the LDA model is computationally demanding due to the size of the corpus. More efficient methods, such as the variational Bayes algorithm of Blei et al. (2003), are applicable. We opt for the Gibbs sampler as it has better convergence properties in our application.

Let $\Omega = \{\Theta, \Phi, \alpha, \eta_1, \dots, \eta_K\}$ denote the set of all model parameters and $\Omega_{-\kappa} = \Omega \setminus \{\kappa\}$ for variable κ and variable set Ω . The Gibbs sampling steps for the model parameters and latent states are as follows. First,

$$p(\theta_d | \Omega_{-\theta_d}, \mathcal{Z}, \mathcal{W}) \propto \prod_{k=1}^K \theta_{d,k}^{\alpha_k - 1 + \sum_{i=1}^V \sum_{n=1}^{N_d} \mathbb{1}(z_{d,n}=k) \mathbb{1}(w_{d,n}=v_i)}, \text{ for } d = 1, \dots, D, \quad (\text{B.6})$$

is proportional to a Dirichlet distribution, as in the conjugate prior in (B.4). Next,

$$p(\phi_k | \Omega_{-\phi_k}, \mathcal{Z}, \mathcal{W}) \propto \prod_{i=1}^V \phi_{k,i}^{\eta_{k,i} - 1 + \sum_{d=1}^D \sum_{n=1}^{N_d} \mathbb{1}(z_{d,n}=k) \mathbb{1}(w_{d,n}=v_i)}, \text{ for } k = 1, \dots, K, \quad (\text{B.7})$$

is proportional to a Dirichlet distribution, as in the conjugate prior in (B.2). Similarly,

$$\begin{aligned}
& p(z_{d,n} = k | \Omega, \mathcal{Z}_{-z_{d,n}}, \mathcal{W}) \\
& \propto \theta_{d,k}^{\alpha_k - 1 + \sum_{i=1}^V \mathbb{1}(w_{d,n}=v_i)} \prod_{i=1}^V \phi_{k,i}^{\eta_{k,i} - 1 + \mathbb{1}(w_{d,n}=v_i)}, \text{ for } k = 1, \dots, K
\end{aligned} \quad (\text{B.8})$$

which is a categorical distribution for $d = 1, \dots, D$ and $n = 1, \dots, N_d$ with probabilities proportional to the right hand side of (B.8).

For the remaining model parameters, $(\boldsymbol{\alpha}, \boldsymbol{\eta}_1, \dots, \boldsymbol{\eta}_K)$, we use the fixed-point iteration (MAP estimator) of Minka (2000); Wallach (2008) at each Gibbs iteration. We optimise $\boldsymbol{\alpha} = a\boldsymbol{\mu}$ as

$$[a\mu_k]^* = a\mu_k \frac{\sum_{d=1}^D \left[\Psi \left(N_d^{(k)} + a\mu_k \right) - \Psi(a\mu_k) \right] + c}{\sum_{d=1}^D \left[\Psi(N_d + a) - \Psi(a) \right] - \frac{1}{s}}, \quad (\text{B.9})$$

and, only in the first step, we optimise η using

$$\eta^* = \frac{\eta \sum_{k=1}^K \sum_{i=1}^V \left[\Psi \left(N^{(k,i)} + \eta \right) - \Psi(\eta) \right] + c}{V \sum_{k=1}^K \left[\Psi \left(\sum_{i=1}^V N^{(k,i)} + V\eta \right) - \Psi(V\eta) \right] - \frac{1}{s}}, \quad (\text{B.10})$$

where $N_d^{(k)} = \sum_{n=1}^{N_d} \mathbb{1}(z_{d,n} = k)$ is the number of tokens assigned to topic k in document d , $N^{(k,i)} = \sum_{d=1}^D \sum_{n=1}^{N_d} \mathbb{1}(w_{d,n} = v_i) \mathbb{1}(z_{d,n} = k)$ is the number of tokens with the term v_i assigned to topic k , and (c, s) are the shape and scale parameters, respectively, for the Gamma priors exemplified in (B.3) and (B.1). The steps in B.9 and B.10 are repeated until convergence⁶. The Gibbs sampler for the proposed 2-step LDA model is outlined in Algorithm 1 below, for a corpus $\mathcal{W}$ obtained from pre-processed data, and K topics.

B.4 Lexicons

Our procedure for constructing priors for the *tax increase* and *tax decrease* topics require specifying the terms whose usage differentiates the two topics. We do that based on reading presidential speeches which are known to provide information about future tax changes. We select a total of 69 speeches used by Romer and Romer (2009) and Yang (2007) in their analyses of tax legislations. The list of the speeches is provided in Appendix D.1. In each speech we note the terms used to announce and motivate changes in particular direction. We then aggregate those results and choose terms whose usage is indicative of discussing a tax change with the particular direction.

Importantly, we do not assume that, for example, a term in the *tax increase* lexicon cannot be used when discussing tax cuts. We use those lexicons only to modify the prior probabilities of those terms in the two topics of interest.

Tax increase: “additional cost”, “additional revenue”, “additional tax”, “balance budget”, “budget deficit”, “cut deficit”, “defense spend”, “deficit”, “deficit reduction”, “fair balance”, “fair share”, “fairness”, “federal revenue”,

⁶Until $\max_k \frac{[a\mu_k]^* - a\mu_k}{a\mu_k} < 0.01$ and $\max_k \frac{\eta^* - \eta}{\eta} < 0.01$

Algorithm 1 Gibbs sampling algorithm

LDA step 1:

- 1: Set $m = 0$, and initialise $\alpha_k^{(m)} = 1$ for $k = 1, \dots, K$ and $\eta = 1$.
- 2: Initialise $\Theta^{(m)}$ using the Dirichlet distribution in (B.4); $z_{d,n}^{(m)}$ for $d = 1, \dots, D$ and $n = 1, \dots, N_d$ using the categorical distribution in (1); $\phi_k^{(m)}$ for all k using the Dirichlet distribution in (B.2).
- 3: Set $\Omega^{(m)} = \{\Theta^{(m)}, \Phi^{(m)}, \alpha^{(m)}, \eta_1^{(m)}, \dots, \eta_K^{(m)}\}$
- 4: **while** $m \leq 15000$ **do**
- 5: Set $m = m + 1$
- 6: Draw $\Theta^{(m)} \mid \Omega_{-\Theta}^{(m-1)}, \mathcal{Z}^{(m-1)}, \mathcal{W}^{(m-1)}$ using the Dirichlet distribution in (B.6)
- 7: Update $\Omega^{(m)} = \{\Theta^{(m)}, \Phi^{(m-1)}, \alpha^{(m-1)}, \eta_1^{(m-1)}, \dots, \eta_K^{(m-1)}\}$
- 8: **for** $k = 1, \dots, K$ **do**
- 9: Draw $\phi_k^{(m)} \mid \Omega_{\phi_k}^{(m)}, \mathcal{Z}^{(m-1)}, \mathcal{W}$ for all k using the Dirichlet distribution in (B.7)
- 10: Update $\Phi^{(m)} = \{\phi_1^{(m)}, \dots, \phi_k^{(m)}, \phi_{k+1}^{(m-1)}, \dots, \phi_K^{(m-1)}\}$
- 11: Update $\Omega^{(m)} = \{\Theta^{(m)}, \Phi^{(m)}, \alpha^{(m-1)}, \eta_1^{(m-1)}, \dots, \eta_K^{(m-1)}\}$
- 12: **end for**
- 13: Set $\mathcal{Z}^{(m)} = \{z_{1,1}^{(m-1)}, \dots, z_{1,N_1}^{(m-1)}, \dots, z_{D,1}^{(m-1)}, \dots, z_{D,N_D}^{(m-1)}\}$
- 14: **for** $d = 1, \dots, D$ **do**
- 15: **for** $n = 1, \dots, N_d$ **do**
- 16: Draw $z_{d,n}^{(m)} \mid \Omega^{(m)}, \mathcal{Z}_{-z_{d,n}}^{(m)}, \mathcal{W}$ using the categorical distribution in (B.8)
- 17: Update $\mathcal{Z}^{(m)} = \{z_{1,1}^{(m)}, \dots, z_{d,n}^{(m)}, z_{d,n+1}^{(m-1)}, \dots, z_{d+1,1}^{(m-1)}, \dots, z_{D,N_D}^{(m-1)}\}$
- 18: **end for**
- 19: **end for**
- 20: Update $\alpha^{(m)} = a\mu$ using the fixed-point iteration in (B.9).
- 21: Set $\eta_k^{(m)} = \eta^{(m)} = a_\eta \iota_V$ where ι_V is a V -dimensional vector of $1/V$. Update $\eta^{(m)}$ using the fixed-point iteration in (B.9).
- 22: **end while**

LDA step 2

- 1: Set $K = K + 1$, set $m = 0$, and initialise $\alpha_k^{(m)} \sim \text{Gamma}^{(m)}(100^{-1}, 100)$ for $k = 1, \dots, K$
 - 2: Set η_k , $k = 1, \dots, K$ from step 1, using equation (2).
 - 3: Initialise $\Theta^{(m)}$ using the Dirichlet distribution in (B.4); $z_{d,n}^{(m)}$ for $d = 1, \dots, D$ and $n = 1, \dots, N_d$ using the categorical distribution in (1); $\phi_k^{(m)}$ for all k using the Dirichlet distribution in (B.2).
 - 4: Set $\Omega^{(m)} = \{\Theta^{(m)}, \Phi^{(m)}, \alpha^{(m)}, \eta_1^{(m)}, \dots, \eta_K^{(m)}\}$
 - 5: Repeat LDA step 1 lines 4–22, except for 21.
-

“fiscal responsibility”, “fiscally responsible”, “government revenue”, “higher tax”, “increase revenue”, “increase tax”, “military spend”, “new spend”, “new tax”, “propose increase”, “propose tax”, “raise revenue”, “raise tax”, “reduce debt”, “reduce deficit”, “revenue increase”, “rise cost”, “sound fiscal”, “tax impose”, “tax increase”, “tax revenue”, “tax rich”

Tax decrease: “boost economy”, “business incentive”, “create incentive”, “create job”, “cut”, “cut propose”, “cut tax”, “ease burden”, “economic growth”, “economic incentive”, “excessive”, “grow economy”, “high rate”, “incentive”, “incentive invest”, “incentivize”, “increase employment”, “increase investment”, “increase production”, “increase productivity”, “increase prosperity”, “investment”, “investment tax”, “lower”, “lower tax”, “new job”, “propose cut”, “provide incentive”, “rate drop”, “rate reduction”, “rebuild economy”, “recession”, “reduce burden”, “reduce rate”, “reduce unemployment”, “reduction”, “relief”, “relief package”, “relief program”, “slow growth”, “stimulate economic”, “stimulate economy”, “stimulate growth”, “stimulate investment”, “strengthen economic”, “strengthen economy”, “tax break”, “tax burden”, “tax credit”, “tax cut”, “tax incentive”, “tax policy”, “tax rate”, “tax rebate”, “tax reduce”, “tax reduction”, “tax relief”

Appendix C Data

C.1 Text data

We analyse the texts of all the documents contained in *The Public Papers of the Presidents*. This includes speeches, but also other public communications (e.g. interviews, letters). We obtained the raw texts from the *American Presidency Project* (www.presidency.ucsb.edu) on 2019-03-25. Our dataset consists of 59,214 texts spanning from 1949-01-20 to 2017-01-19.

The pre-processing starts with breaking the texts into individual paragraphs, resulting in a total of 1,119,200 documents. The text is then broken along non-alphanumeric characters into tokens (individual words). We then remove stopwords - function words such as prepositions and pronouns, since they are not informative in the *bags-of-words* approach; and rare words which appear in less than 20 documents - those are often spelling mistakes, since they are too rare to be informative about the term co-occurrence pattern. The remaining tokens are then lemmatised - all the nouns are turned into singular form and the verbs are turned into present tense first person form. Lastly, we identify meaningful collocations of two words - bigrams. If a combination of two consecutive words (e.g. “tax” and “cut”) appears more often than pre-

dicted by their individual frequency (as measured by a χ^2 score) it is considered a bigram (i.e. “tax_cut”). A bigram is treated as a separate term in the vocabulary and each instance of a bigram in the texts is treated as a single token. The final vocabulary consists of 50,851 terms, including 29,815 bigrams.

C.2 Additional data

We use four series of changes in tax liabilities developed by Romer and Romer (2010). The data-set is part of the paper’s supplementary materials. The construction of their measures is described in the companion background paper (Romer and Romer, 2009). To create the measures they first identify all the major changes in tax liabilities. For each change they analyse the narrative record, including presidential speeches, to determine the motivation behind it. This can be either exogenous to the macroeconomic conditions (deficit-driven or long-run growth) or endogenous (spending-driven or counter-cyclical). The size of the changes is the estimated change in tax liabilities at the time of implementation based on contemporary sources. The changes are timed either at the implementation - when they go into effect, or at enactment - when the legislation is signed by the president, in which case the present value of the changes is given.

We also use the speeches identified by Romer and Romer (2009) as giving motivation behind particular changes to verify the ability of our model to properly classify tax-related content. The list of those speeches is provided in Appendix D.1.

Throughout our analysis we use additional macroeconomic, financial, and tax data. Further information on these data is provided in Table C.1.

Table C.1: Overview of additional variables

Variable	Description	Details/Source
<i>Tax measures:</i>		
Tax Receipts ^a	Federal government current tax receipts	In billions of Dollars, quarterly frequency, seasonally adjusted at annual rate. Source: BEA, account code: W006RC
Income Taxes ^a	Federal government personal income tax receipts	In billions of Dollars, quarterly frequency, seasonally adjusted at annual rate. Source: BEA, account code: A074RC
Corporate Taxes ^a	Federal government corporate income tax receipts	In billions of Dollars, Quarterly Frequency, seasonally adjusted at annual rate. Source: BEA, account code: B075RC
Payroll Taxes ^a	Federal government payroll tax receipts	Contributions for government social insurance in billions of Dollars, quarterly frequency, seasonally adjusted at annual rate. Source: BEA, account code: W780RC

Cyclically Adjusted Revenue	Change in real cyclically adjusted federal government revenues as percent of real GDP	Supplementary material/data of Romer and Romer (2010), variable name in their data file: “DRCARA”
Implicit Tax Rate	Risk-adjusted implicit tax rate with one year maturity as constructed in Leeper et al. (2012)	Leeper et al. (2012) define the implicit tax rate as $1 - Y_m/Y_t$ where Y_m is the yield of a municipal bond and Y_t is the yield of a Treasury bond. We use municipal and treasury bond yields with one year maturity at monthly frequency. Data is taken from the supplementary material of Leeper et al. (2012). We use their provided Matlab code to construct rolling quarterly averages of monthly data.
RR All	RR’s identified endogenous and exogenous tax changes divided by nominal GDP	Supplementary material/data of Romer and Romer (2010), variable name in their data file: “SUMMANRRATIO”
RR Exogenous	RR’s identified deficit-driven and long-run tax changes divided by nominal GDP	Supplementary material/data of Romer and Romer (2010), variable name in their data file: “EXOGENRRATIO”
RR News All	Present value (at time of enactment) of RR’s identified endogenous and exogenous tax changes divided by nominal GDP	Supplementary material/data of Romer and Romer (2010), variable name in their data file: “SUMMAPDVRATIO”
RR News Exogenous	Present value (at time of enactment) of RR’s identified deficit-driven and long-run tax changes divided by nominal GDP	Supplementary material/data of Romer and Romer (2010), variable name in their data file: “EXOGE PDVRATIO”
MR Unanticipated	Mertens and Ravn’s identified exogenous tax changes for which the legislation and implementation date are less than one quarter apart	Supplementary material/data of Mertens and Ravn (2014) obtained from the authors personal webpage. The variable name in their data file is “Tax Narrative”. Retrieved from: https://karelmertens.com/wp-content/uploads/2017/09/jme2014_data.xls

Macroeconomic and financial variables:

GDP ^a	Gross domestic product	In millions of Dollars, quarterly frequency, seasonally adjusted at annual rate. Source: BEA, account code: A191RC
Consumption ^a	Personal consumption expenditures	In millions of Dollars, quarterly frequency, seasonally adjusted at annual rate. Source: BEA, account code: DPCERC
Investment ^a	Gross private investment	In millions of Dollars, quarterly frequency, seasonally adjusted at annual rate. Source: BEA, account code: A006RC
Government Spending ^a	Federal Government current Expenditures	In billions of Dollars, quarterly frequency, seasonally adjusted at annual rate. Source: BEA, account code: W013RC
Government Debt ^{a,b}	Par value of privately held gross federal debt	In millions of Dollars, monthly frequency, not seasonally adjusted, values reported are for the last business day of the month. Source: Federal Reserve Bank of Dallas
3-month T-Bill ^b	Secondary market rate 3-month Treasury bill	Daily frequency (downloaded as monthly averages). Source: Federal Reserve Board, Selected Interest Rates (Daily) - H.15
Federal Funds Rate ^b	Federal funds effective rate	Daily frequency (downloaded as monthly averages). Source: Federal Reserve Board, Selected Interest Rates (Daily) - H.15
Unemployment Rate ^b	Unemployed as percentage of the labor force	Monthly frequency, seasonally adjusted. Source: BLS, series ID: LNS14000000

S&P500 ^{a,b}	S&P composite prices	Composite prices are daily-close, monthly averages. Source: Robert Shiller's US Stock market data, retrieved from https://shillerdata.com
Government Spending News	Nominal present value of Ramey's government spending news variable divided by nominal GDP of previous quarter	Supplementary material/data of Ramey (2011), variable name in her data file: "pdvmily"
<i>Other variables:</i>		
Job Approval of the President ^b	Gallup Approval Poll	Gallup approval poll of the president. Irregular frequency. Source: "The American Presidency Project" at UCSB. Retrieved from : https://www.presidency.ucsb.edu/statistics/data/presidential-job-approval-all-data
Congress Concurrence	Presidential Victories on Votes in Congress	Percentages indicate the number of congressional votes supporting the president divided by the total number of votes on which the president had taken a clear position. The percentages are normalized to eliminate the effects of absences as follows: support = (support)/(support + opposition). Yearly data from 1953 to 2007. Source: Brookings Vital Statistics on Congress, Table 8-1. Retrieved from: https://www.brookings.edu/wp-content/uploads/2017/01/vitalstats_ch8_tbl1.xlsx

a: Variable is expressed in real per capita terms. We use a population measure and the GDP implicit price deflator to transform nominal quantities in real per capita terms. To construct the real per capita data we have used the following two series: (i) Population: Civilian noninstitutional population is defined as persons 16 years of age and older residing in the 50 states and the District of Columbia [thousands of persons], monthly frequency (transformed into quarterly averages), not seasonally adjusted. Source: BLS, series ID: LNU00000000 and (ii) Deflator: Gross Domestic Product: Implicit Price Deflator, Index 2012=100, quarterly frequency, seasonally adjusted. Source: BEA, account code: A191RD

b: Series is transformed into quarterly averages.

Note: BEA stands for *U.S. Bureau of Economic Analysis*; BLS stands for *U.S. Bureau of Labor Statistics*; All data have been accessed and downloaded in June 2020.

Appendix D Topic model results

D.1 Selected tax-related speeches

Romer and Romer (2009) and Yang (2007) use presidential speeches to analyse to motivation behind particular tax legislations. We combine their selection of speeches and use them for two purposes. Firstly, the speeches are used to develop the lexicons of terms related to tax increase and tax decrease, as described in Appendix B.4. Secondly, we use them to verify the ability of our model to properly classify a text based on which direction of tax changes it is discussing.

Below we present a list of speeches announcing legislations whose overall effect was a tax increase (Table D.1) and tax decrease (Table D.2). Importantly, in our estimation we treat individual paragraphs as documents, each having separate mixing proportions. Especially in case of long speeches, such as the *State of the Union Addresses*, many of those paragraphs discuss issues other than taxation. Additionally, certain legislations consisted of measures that increased some taxes, but cut others. In the tables those are indicated as “mixed”. For speeches related to those legislations we expect some paragraphs to have high *tax increase* proportions, and other to have high *tax decrease* proportions. For each speech we therefore show the minimum, the average and the maximum mixing proportion across all of its paragraphs, for both *tax increase* and *tax decrease* topics, as estimated in the second step. Overall the results fit our expectations, supporting the claim that our model is able to distinguish between the direction of the discussed changes.

Table D.1: List of speeches announcing legislation whose net effect was an increase in tax revenue.

Date	Announced legislation	Title of the speech		Tax increase proportion			Tax decrease proportion		
		Mixed	Number of paragraphs	Min.	Av.	Max.	Min.	Av.	Max.
In a special message to Congress on tax policy									
1950/01/23	Revenue Act of 1950	Yes	58	0.010	0.530	0.855	0.004	0.015	0.197
Midyear Economic Report of the President									
1950/07/26	Revenue Act of 1950	Yes	92	0.004	0.383	0.848	0.003	0.059	0.387
Letter to Committee Chairmen on Taxation of Excess Profits									
1950/11/14	Revenue Act of 1950	Yes	9	0.016	0.373	0.788	0.004	0.012	0.027
Annual Budget Message to Congress									
1951/01/15	Revenue Act of 1951	Yes	399	0.002	0.262	0.907	0.002	0.017	0.352
Special Message to the Congress Recommending a "Pay as We Go" Tax Program									
1951/02/02	Revenue Act of 1951	Yes	48	0.019	0.500	0.845	0.004	0.020	0.223
Radio address									
1953/05/19	Extending the Excess Profits Tax Act of 1950	No	76	0.005	0.217	0.759	0.004	0.017	0.060
Annual Message to the Congress on the State of the Union									
1956/01/05	Federal-Aid Highway Act of 1956	No	128	0.004	0.126	0.822	0.002	0.021	0.274
Annual Budget Message to the Congress									
1965/01/25	Social Security Amendments of 1965	No	251	0.006	0.203	0.785	0.003	0.028	0.474
Annual Budget Message to the Congress									
1966/01/24	Tax Adjustment Act of 1966	No	304	0.004	0.177	0.802	0.003	0.024	0.357
Special Message to the Congress on Fiscal Policy									
1966/09/08	Public Law 89-800	No	97	0.007	0.277	0.809	0.003	0.064	0.608
State of Union address									
1967/01/10	Revenue and Expenditure Control Act of 1968	Yes	178	0.004	0.075	0.851	0.004	0.028	0.498
Annual Budget Message to the Congress									
1967/01/24	Revenue and Expenditure Control Act of 1968	Yes	285	0.005	0.176	0.871	0.003	0.024	0.558
Special Message to the Congress: The State of the Budget and the Economy									
1967/08/03	Revenue and Expenditure Control Act of 1968	Yes	130	0.006	0.303	0.776	0.005	0.033	0.498
Annual Budget Message to the Congress									
1968/01/29	Revenue and Expenditure Control Act of 1968	Yes	419	0.004	0.165	0.824	0.003	0.029	0.581
Special Message to Congress on Fiscal Policy									
1969/03/26	Extending the Ten Percent Surtax	No	18	0.124	0.435	0.805	0.005	0.035	0.248
Windfall Profits Tax and Energy Security Trust Fund Message to the Congress									
1979/04/26	Crude Oil Windfall Profit Tax Act of 1980	No	77	0.011	0.304	0.782	0.003	0.019	0.150

Table D.1: List of speeches announcing legislation whose net effect was an increase in tax revenue.

Date	Announced legislation	Title of the speech		Tax increase proportion			Tax decrease proportion		
		Mixed	Number of paragraphs	Min.	Av.	Max.	Min.	Av.	Max.
<i>Statement Announcing the Establishment of the National Commission on Social Security Reform</i>									
1981/12/16	Social Security Amendments of 1983	No	7	0.040	0.302	0.547	0.005	0.009	0.015
<i>State of the Union address</i>									
1982/01/26	Tax Equity and Fiscal Responsibility Act of 1982	No	77	0.004	0.205	0.826	0.003	0.068	0.576
<i>Address Before a Joint Session of the Congress on the State of the Union</i>									
1984/01/25	Deficit Reduction Act of 1984	No	80	0.003	0.116	0.753	0.003	0.030	0.516
<i>Message to the Congress Transmitting the Fiscal Year 1985 Budget</i>									
1984/02/01	Deficit Reduction Act of 1984	No	105	0.003	0.208	0.807	0.002	0.037	0.440
<i>Remarks to Reporters Announcing a Deficit Reduction Plan</i>									
1984/03/15	Deficit Reduction Act of 1984	No	26	0.012	0.184	0.772	0.004	0.016	0.028
<i>Joint Session of Congress on the State of the Union</i>									
1987/01/27	Omnibus Budget Reconciliation Act of 1987	No	34	0.003	0.073	0.631	0.003	0.040	0.682
<i>Statement on Proposed Tax Increases</i>									
1987/10/15	Omnibus Budget Reconciliation Act of 1987	No	4	0.350	0.461	0.618	0.004	0.006	0.010
<i>Statement on the federal budget negotiations</i>									
1990/06/26	Omnibus Budget Reconciliation Act of 1990	No	3	0.010	0.268	0.777	0.008	0.011	0.017
<i>Address to the Nation on the Federal Budget Agreement</i>									
1990/10/02	Omnibus Budget Reconciliation Act of 1990	No	15	0.009	0.261	0.704	0.004	0.057	0.334
<i>Address to the nation on the economic program</i>									
1993/02/15	Omnibus Budget Reconciliation Act of 1993	Yes	20	0.007	0.243	0.740	0.005	0.109	0.666
<i>Address Before a Joint Session of Congress on Administration Goals</i>									
1993/02/17	Omnibus Budget Reconciliation Act of 1993	Yes	75	0.003	0.262	0.789	0.002	0.054	0.634
<i>Radio Address</i>									
1993/05/15	Omnibus Budget Reconciliation Act of 1993	Yes	17	0.006	0.346	0.819	0.005	0.098	0.486

Table D.2: List of speeches announcing legislation whose net effect was a decrease in tax revenue.

Date	Announced legislation	Title of the speech		Tax increase proportion			Tax decrease proportion		
		Mixed	No. paragraphs	Min.	Av.	Max.	Min.	Av.	Max.
<i>Letter to the President of the Senate and to the Speaker of the House of Representatives Urging Continuation of Corporation Tax Rates</i>									
1958/05/26	Tax Rate Extension Act of 1958	No	3	0.008	0.013	0.016	0.011	0.205	0.472
<i>Radio and Television Report to the American People on the State of the National Economy</i>									
1962/08/13	Changes in Depreciation Guidelines and Revenue Act of 1962	Yes	68	0.004	0.150	0.750	0.005	0.218	0.744
<i>Annual Message to the Congress on the State of the Union</i>									
1963/01/14	Revenue Act of 1964	Yes	86	0.002	0.037	0.525	0.003	0.120	0.895
<i>Special Message to the Congress on Tax Reduction and Reform</i>									
1963/01/24	Revenue Act of 1964	Yes	145	0.002	0.025	0.331	0.011	0.572	0.899
<i>Remarks at the National Conference of the Business Committee for Tax Reduction</i>									
1963/09/10	Changes in Depreciation Guidelines and Revenue Act of 1962	Yes	36	0.004	0.078	0.590	0.012	0.452	0.847
<i>Remarks Upon Announcing Plans to Recommend a Reduction in Excise Taxes</i>									
1965/05/15	Excise Tax Reduction Act of 1965	No	14	0.007	0.132	0.571	0.010	0.252	0.647
<i>Special Message to the Congress Recommending Reduction of Excise Taxes and Increases in User Charges</i>									
1965/05/17	Excise Tax Reduction Act of 1965	No	112	0.003	0.048	0.579	0.011	0.311	0.729
<i>Special Message to the Congress Recommending Reinstatement of the Investment Tax Credit and Accelerated Depreciation Investment Incentives</i>									
1967/03/09	Public Law 90-26	Yes	33	0.008	0.090	0.546	0.007	0.202	0.668
<i>Special Message to the Congress on Reform of the Federal Tax System</i>									
1969/04/21	Tax Reform Act of 1969	No	38	0.004	0.044	0.434	0.022	0.400	0.786
<i>Statement Announcing Changes in Administration of the Depreciation Provisions of the Tax Laws</i>									
1971/01/11	Reform of Depreciation Rules	No	17	0.005	0.067	0.337	0.012	0.300	0.801
<i>Annual Budget Message to the Congress</i>									
1971/01/29	Reform of Depreciation Rules	No	224	0.003	0.023	0.524	0.005	0.140	0.794
<i>Challenge of Peace</i>									
1971/08/15	Revenue Act of 1971	No	56	0.006	0.090	0.395	0.004	0.125	0.652
<i>Address to the Nation on Energy and Economic Programs</i>									
1975/01/13	Tax Reduction Act of 1975	Yes	41	0.005	0.062	0.499	0.009	0.203	0.818
<i>Address Before a Joint Session of the Congress Reporting on the State of the Union</i>									
1975/01/15	Tax Reduction Act of 1975	Yes	91	0.003	0.040	0.622	0.005	0.188	0.748
<i>Annual Budget Message to the Congress</i>									
1975/02/03	Tax Reduction Act of 1975	Yes	89	0.002	0.033	0.449	0.003	0.319	0.875
<i>Address to the Nation on Federal Tax and Spending Reduction</i>									
1975/10/06	Revenue Adjustment Act of 1975	No	28	0.003	0.081	0.439	0.013	0.337	0.766
<i>Annual Message to Congress</i>									
1976/01/26	Tax Reform Act of 1976	No	24	0.002	0.130	0.737	0.002	0.168	0.687
<i>Economic Recovery Program—Message to the Congress</i>									

Table D.2: List of speeches announcing legislation whose net effect was a decrease in tax revenue.

Date	Announced legislation	Title of the speech		Tax increase proportion			Tax decrease proportion		
		Mixed	No. paragraphs	Min.	Av.	Max.	Min.	Av.	Max.
1977/01/31	Tax Reduction and Simplification Act of 1977	Yes	34	0.007	0.056	0.458	0.022	0.334	0.711
	<i>Fiscal Year 1978 Budget Revisions Message to the Congress Transmitting the Revisions</i>								
1977/02/22	Tax Reduction and Simplification Act of 1977	Yes	13	0.004	0.027	0.126	0.013	0.286	0.696
	<i>State of the Union address</i>								
1978/01/19	Revenue Act of 1978	No	305	0.003	0.028	0.616	0.002	0.085	0.695
	<i>Tax Reduction and Reform Message to the Congress</i>								
1978/01/20	Revenue Act of 1978	No	204	0.003	0.042	0.533	0.018	0.432	0.870
	<i>Budget Message to the Congress Transmitting the Fiscal Year 1979 Budget</i>								
1978/01/20	Revenue Act of 1978	No	35	0.003	0.025	0.168	0.004	0.187	0.751
	<i>Inaugural Address</i>								
1981/01/20	Economic Recovery Tax Act of 1981	Yes	35	0.004	0.022	0.336	0.004	0.054	0.471
	<i>Address to the Nation on the Economy</i>								
1981/02/05	Economic Recovery Tax Act of 1981	Yes	50	0.004	0.080	0.624	0.008	0.349	0.775
	<i>Address before a Joint Session of the Congress on the Program for Economic Recovery</i>								
1981/02/18	Economic Recovery Tax Act of 1981	Yes	63	0.004	0.082	0.645	0.005	0.329	0.778
	<i>Address Before a Joint Session of the Congress on the Program for Economic Recovery</i>								
1981/04/28	Economic Recovery Tax Act of 1981	Yes	40	0.004	0.053	0.762	0.005	0.201	0.820
	<i>Address to the Nation on Tax Reform</i>								
1985/05/28	Tax Reform Act of 1986	Yes	53	0.003	0.057	0.402	0.005	0.360	0.818
	<i>Address Before a Joint Session of Congress on the State of the Union</i>								
1986/02/04	Tax Reform Act of 1986	Yes	34	0.002	0.028	0.451	0.003	0.115	0.750
	<i>Radio Address to the Nation on Tax Reform</i>								
1986/05/10	Tax Reform Act of 1986	Yes	7	0.006	0.051	0.205	0.015	0.376	0.738
	<i>The President's Radio Address</i>								
1997/02/22	Taxpayer Relief Act of 1997 and Balanced Budget Act of 1997	Yes	8	0.003	0.119	0.530	0.009	0.354	0.865
	<i>Remarks on Departure for Boston</i>								
1997/06/30	Taxpayer Relief Act of 1997 and Balanced Budget Act of 1997	Yes	40	0.005	0.067	0.487	0.003	0.236	0.760
	<i>A press conference</i>								
2001/02/05	Economic Growth and Tax Relief Reconciliation Act of 2001	No	20	0.009	0.043	0.188	0.008	0.397	0.740
	<i>The President's Agenda for Tax Relief</i>								
2001/02/08	Economic Growth and Tax Relief Reconciliation Act of 2001	No	1	0.129	0.129	0.129	0.207	0.207	0.207
	<i>The President's Radio Address</i>								

Table D.2: List of speeches announcing legislation whose net effect was a decrease in tax revenue.

Date	Announced legislation	Title of the speech		Tax increase proportion			Tax decrease proportion		
		Mixed	No. paragraphs	Min.	Av.	Max.	Min.	Av.	Max.
2001/03/17	Economic Growth and Tax Relief Reconciliation Act of 2001	No	10	0.010	0.169	0.615	0.083	0.303	0.738
	<i>Remarks to Business</i>								
2001/10/26	Job Creation and Worker Assistance Act of 2002	Yes	43	0.005	0.054	0.426	0.003	0.084	0.745
	<i>State of the Union address</i>								
2002/01/29	Job Creation and Worker Assistance Act of 2002	Yes	64	0.003	0.034	0.689	0.003	0.051	0.680
	<i>Remarks to the Economic Club of Chicago in Chicago</i>								
2003/01/07	Jobs and Growth Tax Relief Reconciliation Act of 2003	Yes	52	0.003	0.114	0.702	0.004	0.223	0.815
	<i>The President's Radio Address</i>								
2003/01/11	Jobs and Growth Tax Relief Reconciliation Act of 2003	Yes	11	0.008	0.086	0.396	0.011	0.226	0.795
	<i>Remarks to the Tax Relief Coalition</i>								
2003/05/06	Jobs and Growth Tax Relief Reconciliation Act of 2003	Yes	47	0.004	0.090	0.748	0.004	0.194	0.839
	<i>State of the Union address</i>								
2004/01/20	Working Families Tax Relief Act of 2004	No	68	0.004	0.050	0.728	0.004	0.058	0.747
	<i>Remarks on the national economy</i>								
2008/01/18	Economic Stimulus Act of 2008	No	14	0.004	0.094	0.563	0.007	0.182	0.824

D.2 Wordclouds - composition of the topics

Figure D.2 shows the 26 topic distributions estimated in the second step of our LDA approach in the form of wordclouds. For each topic 150 terms with the highest probability of being used are shown. The size of a term indicates its relative probability. For each topic we provide an interpretation which we believe best captures its likely usage. As expected the majority of estimated topics relate to particular issues in U.S. politics. It is important to note however that this is not the case for all of them. Topics are based on terms that tend to co-occur in the documents, and that co-occurrence can be caused not only by the what issues are discussed. For example, our data-set includes interviews with the president, and the particular language used in those seems to “picked up” by topic shown in Fig. D.2o. Another example is the topic which we call *Informal Speech* shown in Fig. D.2l. The fact that it heavily features the term “laughter” used in the transcripts to indicate when the president or the audience is laughing - suggests that it concerns the informal part of presidential speeches. Other terms however do not seem to be connected by any particular theme, and as such, it might be an artifact of our pre-processing approach. In particular, terms that show up frequently regardless of the actual content might co-occur “naturally” and be grouped into a common topic.

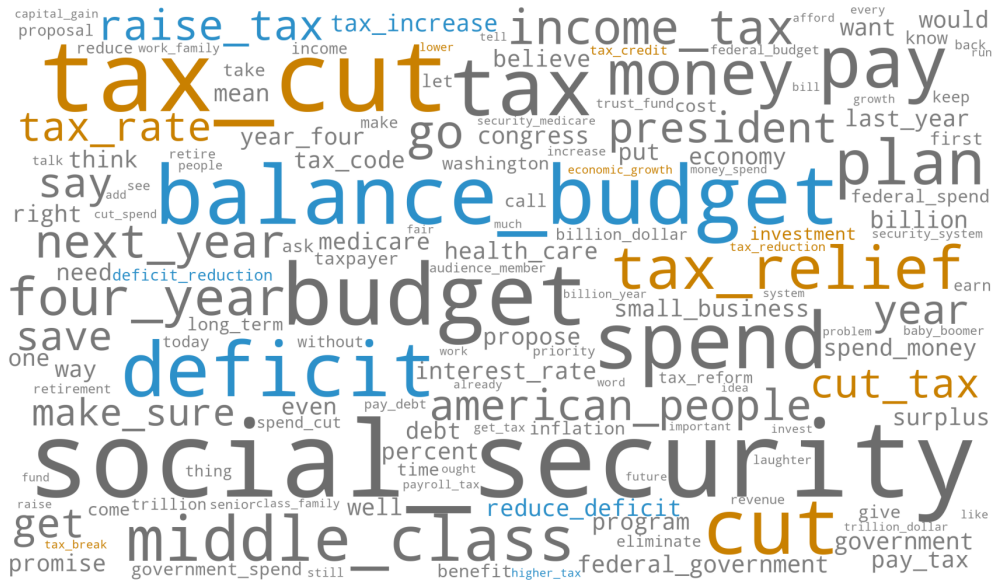
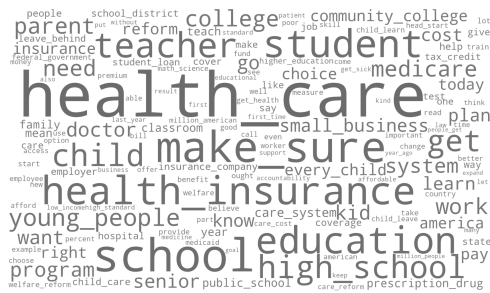


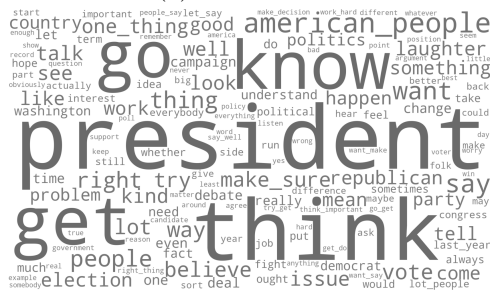
Figure D.1: General tax topic from the (unsupervised) first step LDA.



(a) Social Services



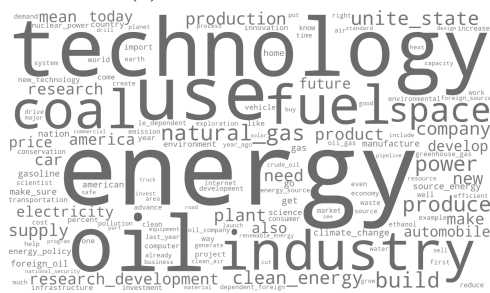
(b) Legislative Process



(c) Persuasive Rhetoric



(d) Public Administration



(e) Natural Resources, Energy & Technology



(f) Health Care

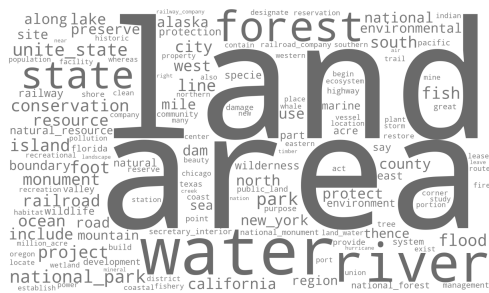


(g) Proclamations of Unity & Patriotism

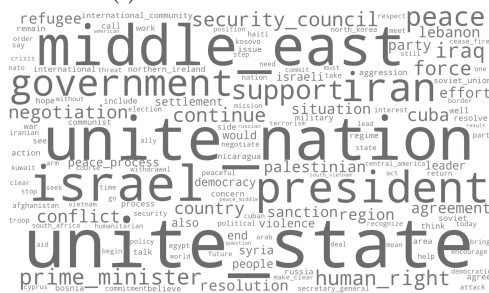


(h) Cold War

Figure D.2: Wordclouds of the non-tax topics



(i) Nature & Environment



(k) Middle East



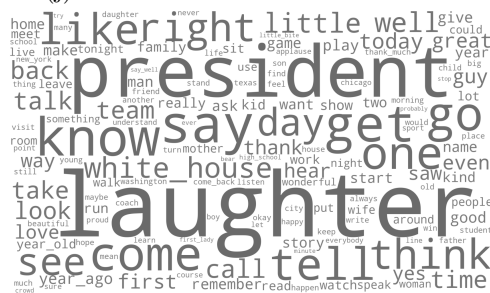
(m) Executive Orders



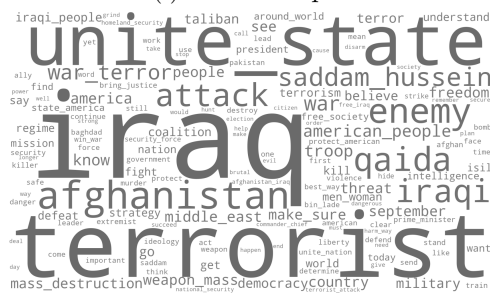
(o) Interviews



(j) Tradition and Conservative Values



(1) Informal Speech

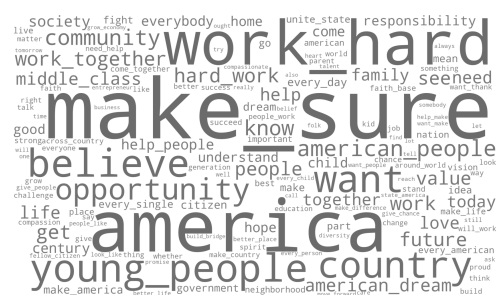


(n) War on Terror



(p) Crime

Figure D.2: Wordclouds of the non-tax topics



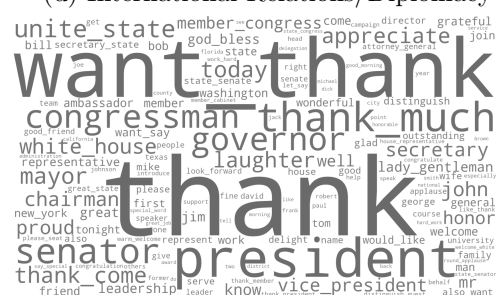
(q) American Values



(s) National Security & Emergencies



(u) International Relations/Diplomacy



(w) Expressing Gratitude in Speeches



(r) Paying Respect to Armed Forces



(t) Economic Development



(v) Freedom & Patriotism



(x) International Economics & Trade

Figure D.2: Wordclouds of the non-tax topics

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