Online Appendix
"Partisanship and Fiscal Policy in Economic Unions: Evidence from U.S. States"

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A Data Appendix

In this appendix, we describe the core data sets we use and how we process the data for analysis.

A.1 Fiscal variable definitions

We collect comprehensive data on revenues and expenditures for all states from the U.S. Census Bureau's State and Local Government Finance historical database for 1958 to 2006 by fiscal year. For both expenditures and revenues, the State and Local Government Finance database provides detailed accounts for the end use and source of financing, including purpose of intergovernmental transfers as well as type of spending. The data for 2007-2014 come from the Census' Annual Surveys of State and Local Government Finances. See the Data Availability Statement Table RM.1 in the `ReadMe` for URLs.[1]

Our fiscal variables follow U.S. Census Bureau (n.d.*b*) definitions. Our measure of government expenditures is called "Total Expenditure." The Census defines it as "including] all amounts of money paid out by a government during its fiscal year [...] other than for retirement of debt, purchase of investment securities, extension of loans, and agency or private trust transactions," see (U.S. Census Bureau, n.d.*b*, p. 5-1) This measure is the sum of current operating expenditures, total capital outlays, total spending on assistance and subsidies, total insurance trust benefits, total interest on debt, and total intergovernmental expenditures.

In the beginning of our work, we show that revenues are balanced. We first consider "General Revenues," which Census defines as "revenue from external sources and expenditures to individuals or agencies outside the government." The Census breaks down general revenue by categories; we also exploit the Census Bureau's taxonomy of taxes. In particular, we consider "General Sales and Gross Receipts Taxes" as a measure of sales tax revenue and "Individual Income Taxes" as a measure of personal income tax revenue.

We also use "total debt" from the census data set. The weakness of this measure is that it is based on the face value of outstanding debt, rather than its market value. However, by focusing on the change in total debt we should limit the importance of the composition problem of debt.

Economic activity. We also use data on state GDP and population found in the U.S. Bureau of Economic Analysis' Regional Economic Accounts by calendar year.

[1] We do not use the preliminary estimate for 2015 because we found that preliminary estimates can be off substantially in 2007 and 2008, when the historical and contemporaneous sources overlap.

Governor Data. Our gubernatorial data is based on The Council of State Governments (2020), as detailed in the Data Availability Statement Table RM.5 in the `ReadMe`.

Timing of partisanship. We assign the political status of the state to be that in the first quarter of the calendar year preceding the fiscal year, as it is in the middle of the budget process.

Macroeconomic data. We use the aggregate annual GDP deflator to deflate all nominal variables in our state-level data set. In addition, we collect quarterly data on grants-in-aid to both state and local governments, and on federal, and state and local government expenditures as well as consumption, investment expenditures, and aggregate GDP, and measures of debt ratings, unemployment, and aggregate recessions.

We provide a list of variables used in the analysis of state-level panel data from non-Census sources:

- Annual GDP deflator: NIPA data (U.S. Bureau of Economic Analysis, n.d.*a*) via FRED, see the Data Availability Statement Table RM.4 in the `ReadMe`.
- Aggregate Recession indicator: Federal Reserve Bank of St. Louis (n.d.).
- State GDP: Regional accounts (U.S. Bureau of Economic Analysis, n.d.*b*), see the Data Availability Statement Table RM.7 in the `ReadMe`.
- State population: BEA Regional accounts (U.S. Bureau of Economic Analysis, n.d.*b*), see the Data Availability Statement Table RM.7 in the `ReadMe`.
- State unemployment rates: U.S. Bureau of Labor Statistics (n.d.). See the Data Availability Statement Table RM.6 in the `ReadMe`.
- State debt ratings: S&P Global Ratings (n.d.).

A.2 FAADS Data Appendix

A.2.1 Motivation

A difficulty with quantifying the effect of federal transfers to states is that oftentimes federal transfers are contingent on state spending; states must allocate some level of funds to a program in order to receive federal assistance. As a result, state expenditures partially determine the level of federal aid states receive and, of course, how much aid states receive, will factor into how much they spend. This raises endogeneity issues when trying to identify the effect of intergovernmental grants on state spending. One way to address this concern is purging federal aid of programs that have matching requirements, where every dollar of state spending leads to more federal funds. To identify these programs, we leverage transaction level data from the Federal Assistance Award Data System (FAADS). The granularity of this data allows us to disregard programs that have matching requirements and isolate aid that can be treated as largely independent of state spending.

A.2.2 Overview

In the FAADS data, each transaction is tied to a unique Catalog of Federal Domestic Assistance (CFDA) number which serves as a program identifier. We then determine whether each program contains matching requirements by leveraging two additional sources. Our first approach is to use historical and current assistance listing data provided by SAM (n.d.), see the Data Availability Statement Table RM.3 in the `ReadMe`. The historical assistance listing data provides a brief description of a program's matching requirements, while the current assistance listing data includes an indicator variable for whether each program has matching requirements. Our second approach is to employ basic text parsing of the annual CFDA publication, which provides a detailed description of the active programs in that year and is available on the same website. In particular, we search for text phrases in the *Formula and Matching Requirements* section of the catalog to classify programs as having matching requirements or being match-free.

One difficulty is that both the CFDA parsing and the assistance listing data are primarily focused on currently active or recently terminated programs, with substantially less coverage of older programs. Since the beginning of our analysis in 1983, many programs have split, merged, or transferred to other departments. Therefore, to extend this analysis over all the years in our sample we link programs across time by leveraging the appendix of the 2009 CFDA (SAM (n.d.)). that includes a detailed history of each program. To be specific, we generate a group identifier for any programs that have ever been related to one another across our sample period. Then we take a conservative approach and disregard any of the program groups which contain one or more programs that have been identified as having matching requirements by either method.

A.2.3 FAADS Data

We retrieved the FAADS data from FY 1983 to FY 2010 from the U.S. Census Bureau (n.d.*a*) in the form of quarterly text files – see the Data Availability Statement Table RM.2 in the `ReadMe` for links. Some sources have noted that the quality of FAADS may be somewhat variable[2] Additionally there may also be an issue with initial recipient vs place of performance for some programs. The `2010 User Guide` notes that "Reporting in FAADS is based on the geographic location of the initial recipient. This may be different from the location of the funded project and could also be different from the location of secondary recipients or the prime beneficiaries."

A.2.4 Processing

- The FAADS data was read with a simple python script that identified fields based on their text position.
- Some small errors were present:
  - In the correction indicator field, there should only be values of "C", "L", or missing but there are several other values the field takes on. However, the incidence of

[2]For further information see Bass (2006).

this is very small making up less than .01% of records. Corrected or late entries are moved to the correct fiscal year in cases of C or L, and other indicator errors are left as is. The majority of this is due to the Corporation for National and Community Service in 2000.

  - A similar issue occurs with the recipient type field, where the field takes values that are not part of the standard coding. This problem is minor and occurs in less than .01% of records.
  - Around .5% of records are missing the total amount and are treated as zeros.
  - Around .03% of records are missing the state name and are dropped from the data set.

- The type of assistance and the recipient type are not consistent within a program number. This is not necessarily an error so much as a feature of the data. Some programs have multiple ways to distribute aid and allow different recipient types to apply for funds. When aggregating, within each program federal funds are divided by whether or not the recipient was a state. We also calculate the share of federal funds that are awarded to a state vs all recipient types for each program. We use the funds marked as going to states.
- We limit our analysis to grant type aid (codes 02, 03, and 04) this includes Block, Project, and Formula grants, respectively.
- Finally, the FAADS data uses federal fiscal years from October 1st through September 30th the following year. We adjust the data to correspond with state fiscal years, which generally run July 1st through June 30th.

A.2.5 External Checks

We compared the FAADS data set to the Consolidated Federal Funds Report (CFFR) data, which can also be found as text files on the National Archives website. While some additional agencies report to CFFR, the two data sets can be merged on the state-year-program level. Among successfully merged records 90% of the federal amounts were an exact match between the two data sets. We also compared data to an the congressional testimony of Bass (2006) in Table A.2.1.

Crosswalk of Programs Since many programs split or merge or are renamed over the sample period, we constructed group identifiers that include any programs that have ever been linked to one another. These were constructed by parsing the 2009 CFDA catalogue which contains a detailed program history in the appendix. For example, if a program history said "13.992 Alcohol and Drug Abuse and Mental Health Services Block Grant (1982B) Number changed to 93.992 (1990U)" then the CFDA numbers 13.992 and 93.992 would be grouped under one program ID number.

OMB Watch Tabulation

Type	Aggregate	Action	Total
Direct with unrestricted use	3219.78	0.16	3219.94
Insurance 2560.00	0.01	2650.01	
Direct for specified use	1660.78	269.92	1930.70
Block and formula	1088.14	653.73	1741.87
Directed & guaranteed/insured loans	727.03	195.68	922.71
Project grants & coop agreements	17.35	484.89	500.24
Other	6.43	0.47	6.90

Source: Values as reported in Bass (2006, Table 1).

Replication

Type	Aggregate	Action	Total
Direct with unrestricted use	3176.814	0.158	3176.972
Insurance	3098.105	0.009	3098.114
Direct for specified use	1661.334	269.919	1931.253
Block and formula	1094.917	653.726	1748.643
Direct & guaranteed/insured loans	727.034	195.684	922.717
Project grants & coop agreements	17.355	481.317	498.672
Other	6.426	0.423	6.849

Table A.2.1: Quality Check of FAADS Data Processing: Replicating OMB Watch Descriptive Statistics (Bass, 2006)

Identification of Exogenous Aid To identify whether program IDs have matching requirements, we use two primary data sources. The source is SAM (n.d.) (see the ReadMe for specific URLs). There, we downloaded the current assistance listings and historical assistance listings. The current assistance listings have an indicator variable that describes whether a program has matching requirements, while the historical listings have a text field that details matching requirements. With the historical listings, the language is very standard therefore the following simple sentences can be used to identify programs that have matching requirements:

- No matching requirements: "Matching requirements are not applicable to this program", "This program has no matching requirements", or "There are no matching or cost sharing requirements."

The second source is the 2008 CFDA Catalog (also available on `https://sam.gov/content/assistance-listings`, see the ReadMe for specific URLs) that has a text field called "Formula and Matching requirements".

Here the language used to describe formula and matching requirements is more diverse than with the assistance listing data, but the idea is similar with key phrases being used to identify whether a program has matching requirements. In general, the three methods of identifying programs with matching requirements align closely.

- The correspondence is 97% for the the two methods using assistance listing data when both are not missing

- The correspondence is 96% between all three methods when none are missing

Finally, we limited our data to the hundred largest program IDs, or groupings of CFDA numbers that were never identified as having matching requirements. Examining these descriptions, we make two additional changes – removing Unemployment Insurance and including the Community Services Block Grant. For the final dataset, we aggregate the federal amount of these programs where the recipient is listed as a state and the program was identified as match-free by at least one of the methods described above.

Table A.2.2: Table of FAADS Program Classification

CFDA	Millions ($)	Program Name	Included
93.778	107209	Medical Assistance Program	0
20.205	32380	Highway Research Planning And Construction	0
13.714	13290	Medical Assistance Program	0
93.558	8193	Temporary Assistance For Needy Families	1
84.010	7996	Title I Grants To Local Education Agencies	1
10.555	7570	National School Lunch Program	0
84.027	4973	Handicapped-State Grants	1
10.557	4221	Special Supplemental Food Program For Women Infants And Children	1
93.658	3504	Foster Care Title IV E	0
93.560	2802	Family Support Payments To States-Assistance Payments	0
10.561	2552	State Administrative Matching Grants For Food Stamp Program	0
13.780	2458	Assistance Payments Maintenance Assistance	0
17.250	2363	JTPA Title II	1
13.808	2187	Assistance Payments - Maintenance Assistance	0
14.228	2110	Community Development Block Grants/State's Program	1
93.767	2047	State Children's Insurance Program (CHIP)	0
93.667	2014	Social Services Block Grant	1
84.126	1971	Rehabilitation Services-Vocational Rehabilitation Grants To States	0
93.563	1844	Child Support Enforcement	0
83.516	1679	Disaster Assistance	0
93.568	1673	Low Income Home Energy Assistance	1
93.596	1580	Child Care Mandatory & Matching Funds Of The Child Care & Dev. Fund	0
13.667	1357	Social Services Block Grant	1
93.020	1342	Family Support Payments To States-Assistance Payments	0
10.558	1233	Child And Adult Care Food Program	1
93.959	1202	Block Grants For Prevention And Treatment Of Substance Abuse	1
66.458	1184	Capitalization Grants For State Revolving Funds	0
93.575	1122	Child Care And Development Block Grant	1
84.048	1106	Vocational Education_Basic Grants To States	0
17.207	1097	Employment Service	1
93.659	1008	Adoption Assistance	0
84.394	999	State Fiscal Stabilization Fund (SFSF)-Education State Grants	0
10.553	961	School Breakfast Program	1
14.239	953	Home Investment In Affordable Housing	0
84.367	873	Improving Teacher Quality State Grants	1
97.036	739	Disaster Grants - Public Assistance (Presidential Declared Disasters)	0
20.507	568	Federal Transit-Formula Grants	0
13.818	548	Low Income Home Energy Assistance	1
93.917	540	HIV Care Formula Grants	0

93.994	515	Maternal And Child Health Services Block Grant	0
20.500	501	Urban Mass Transportation Capital Improvement Grants	0
17.260	483	Dislocated Workers	1
81.042	461	Weatherization Assistance For Low-Income Persons	1
66.468	460	Capitalization Grants For Drinking Water State Revolving Fund	0
93.045	446	Special Programs For The Aging-Title III, Part C-Nutrition Services	0
17.245	400	Trade Adjustment Assistance-Workers	1
84.011	392	Migrant Education Program_State Formula Grant Program	1
84.186	387	Drug Free Schools And Communities-State Grants	0
13.789	367	Low Income Energy Assistance	1
84.002	366	Adult Education-State-Administered Program	0
93.268	354	Childhood Immunization Grants	1
13.960	352	Social Security Payments To States For Determination Of Disability	0
16.579	345	State And Local Narcotics Control Assistance	0
13.658	332	Foster Care Title IV-E	0
14.850	326	Public And Indian Housing	1
17.259	325	WIA Youth Activities	1
84.173	322	Handicapped-Preschool Incentive Grants	1
84.397	320	State Fiscal Stabilization Fund (SFSF)-Government Services Recovery Act	0
17.246	317	Employment And Training Assistance-Dislocated Workers	1
20.106	307	Airport Improvement Program	0
17.258	298	WIA Adult Program	1
13.992	296	Alcohol And Drug Abuse And Mental Health Services Block Grant	0
84.151	286	Federal State And Local Partnerships For Educational Improvement	0
97.067	284	Homeland Security Grant Program	1
93.044	277	Special Prog. For The Aging-Title III, Part B-Grants For Supportive Servc	0
93.958	269	Block Grants For Community Mental Health Services	1
93.645	258	Child Welfare Services_State Grants	0
84.287	256	21st Century Community Learning Centers	1
15.252	252	Abandoned Mine Land Reclamation Program	1
93.855	248	Allergy Immunology And Transplantation Research	1
84.181	247	Special Education-Grants For Infants And Families With Disabilities	0
84.357	242	Reading First State Grants	0
20.509	239	Public Transportation For Nonurbanized Areas	0
64.015	231	Veterans State Nursing Home Care	1
16.575	221	Crime Victim Assistance	1
93.859	220	Pharmacology Physiology And Biological Chemistry Research	1
10.665	217	Schools And Roads_Grants To States	0
93.556	215	Promoting Safe And Stable Families	0
13.783	208	Child Support Enforcement	0

84.391	204	Special Education Grants To State - Recovery Act	0
13.635	201	Special Programs For The Aging_Title III_Part C_Nutrition Services	0
13.994	194	Maternal And Child Health Services Block Grant 0180	0
93.561	189	Job Opportunities And Basic Skills Training	0
17.255	181	Workforce Investment Act	1
84.365	180	English Language Acquisition Grants	1
20.600	179	State And Community Highway Safety	0
10.559	176	Summer Food Service Program For Children	1
84.389	174	Title I Grants To Local Educational Agencies Recovery Act	0
84.318	165	Technology Literacy Challenge Fund	0
93.028	156	Low Income Home Energy Assistance	1
84.268	154	Federal Direct Student Loan Program	1
93.960	149	Social Security Payments To States For Determination Of Disability	1
93.940	149	HIV Prevention Activities–Health Department Based	1
66.605	147	Performance Partnership	0
81.041	145	State Energy Conservation	0
93.389	142	Research Infrastructure	1
84.340	140	Class Size Reduction	0
93.853	140	Extramural Research Program In The Neurosciences And Neurological Disorder	1
13.633	136	Special Programs For The Aging Title III Parts A And B Grants	0
93.847	134	Diabetes Endocrinology And Metabolism Research	1

A.3 Bonica Campaign Finance

We use the recipient-level campaign finance data from Bonica (2016) to compare the political ideology of gubernatorial candidates. Bonica (2014) constructs a quantitative measure of gubernatorial ideology by looking at common donors to each governor–assigning a negative score for Democratic governors and positive for Republican governors. We use the difference between the campaign finance (CF) score of Republican and Democratic candidates of the general election as a measure of "treatment intensity." Bonica (2014) constructs campaign-finance measures using correspondent analysis, essentially identifying the primary dimension along which donors or recipients cluster. One cluster that emerges is associated with Democratic candidates with largely negative CF scores, and one with Republican candidates with largely positive CF scores. We propose to use the difference between the CF scores of Republican and Democratic candidates of the general election as a measure of "treatment intensity." Focusing on the difference between CF scores has the advantage of offsetting any common location-shift in ideology due to the common state or time of the election.[3]

Of all recipients, we keep only Republican and Democratic candidates for governor, and also keep only those who are explicitly flagged as having run in the general election, or those who are incumbents, or those with general election information (flagged as either general election winners or losers, and with a positive number of votes in the general election). We also drop those without dynamic recipient campaign finance scores or with missing information on the number of givers, or with negative individual contributions. Next, we reshape the data set into an election-level data set, keeping only observations with exactly two candidates – as some elections are uncontested, and on some occasions more than one candidate from one party may run in a general election, for example in some Louisiana races. We end up with an unbalanced panel for all fifty states starting in 1990 for many states.

[3]We focus on governors with at least eight donors, since Bonica (2016) points out that with few givers the estimated CF score can be unreliable – and the codebook names eight as the cutoff. In some instances, the information in Bonica (2016) does not allow us to identify unique winners or losers – for example, due to the jungle primary in Louisiana, or due to errors or missing information such as listing multiple primary candidate winners in other states. When apparent in visual inspection of the data, we used information from Wikipedia to adjust data on 7 elections (AK 1990, OR 1994, GA 1998, LA 2000, CA 2003, UT 2008, WI 2012).

B Methodology Appendix

This appendix details (a) a simulation study of the validity of our estimators in this context in Section B.1, (b) a proof of identification assumptions in Section B.2, and (c) an overview of our local randomization approach in Section C.1

B.1 Monte Carlo assessing the different estimators

The analysis in Calonico, Cattaneo and Titiunik (2014) applies to a simpler RDD framework than ours in equation 2.1; namely one without IG aid interactions. While we believe that their results are likely applicable to our setting, we use simulation evidence to verify that this is the case for a data-generating process such as ours.

Specifically, we fit a 5th order polynomial to all elections in our data, following model (2.2) but with $q = 5$, instead of $q = 2$ as in the main model. The results vary little, even when removing fixed effects. We focus our simulation exercise on the interaction term with positive IG aid and thus keep all observations with positive IG growth. The residuals and the RHS variable are saved for later use. Next, we simulate

$$
\begin{aligned}
y_{s,t}^{(i)} = &\sum_{p=0}^{5}(c_p^{+} MOV_{\tilde{s}(i),\tilde{t}(i)}^{p} + c_{IG,p}^{+} \Delta IG_{\hat{s}(i),\hat{t}(i)} MOV_{\tilde{s}(i),\tilde{t}(i)}^{p}) \times (MOV_{\tilde{s}(i),\tilde{t}(i)}^{p} > 0) \\
&+ \sum_{p=0}^{5}(c_p^{-} MOV_{\tilde{s}(i),\tilde{t}(i)}^{p} + c_{IG,p}^{-} \Delta IG_{\hat{s}(i),\hat{t}(i)} MOV_{\tilde{s}(i),\tilde{t}(i)}^{p}) \times (MOV_{\tilde{s}(i),\tilde{t}(i)}^{p} \leq 0) + u_{\dot{s}(i),\dot{t}(i)}
\end{aligned}
$$

The MOV, IG growth, and residuals are sampled *iid* for a total sample size of 500. We repeat this process 1,000 times. For each simulation, we calibrate the MOV bandwidth using the leave-one-out MSE method and different methods from Calonico, Cattaneo and Titiunik (2014) for a standard RDD without interaction term. A linear MOV controls and a robust (in this case quadratic) MOV control are applied to the calibrated bandwidth, and we report the true coverage rates for a nominal 90% confidence interval.

Table B.1 reports the simulation results. For each estimator (linear or quadratic MOV control) and choice of bandwidth (i.e., the maximum absolute MOV), the table reports the average bandwidth chosen, the actual coverage rate (ideally, 90%), and the average length of the confidence interval. The top two rows show the main procedure. The linear RDD estimator has a coverage of 82.1%, and tends to pick an MOV bandwidth around 10.45pp. Reassuringly, this value is in between the 10pp and 11pp bandwidths the estimator picks for our baseline model with or without fixed effects. The confidence interval is, on average, 0.246 (in elasticity terms) long. Our preferred (baseline) robust (quadratic) estimator, has a higher coverage, of 86.9%, close to the nominal 90%, but it comes at the cost of a longer confidence interval of length 0.404.

The next set of results uses undersmoothing by choosing the bandwidth using the *rdbwselect* package in Stata that implements four different methods from Calonico, Cattaneo and Titiunik (2014) to calibrate the MOV bandwidth for a standard RDD and applies a linear estimator to that setting. Last, it compares taking the minimum bandwidth across four

Table B.1: Monte Carlo: Average bandwidths, coverage, and length of confidence interval of our estimator for a nominal coverage of 90% for different bandwidth selection procedures and MOV polynomials

Bandwidth selection	Polynomial degree	Avg bandwidth (decimal)	Coverage (decimal)	Avg length of CI (decimal)
CV	1.000	0.107	0.822	0.280
CV	2.000	0.107	0.875	0.467
CER-RD	1.000	0.072	0.851	0.323
CER-RD	2.000	0.072	0.844	0.532
CER-sum	1.000	0.068	0.866	0.338
CER-sum	2.000	0.068	0.847	0.561
MSE-RD	1.000	0.099	0.851	0.273
MSE-RD	2.000	0.099	0.875	0.439
MSE-sum	1.000	0.093	0.839	0.283
MSE-sum	2.000	0.093	0.865	0.456
Min-across-CER-and-MSE	1.000	0.067	0.863	0.341
Min-across-CER-and-MSE	2.000	0.067	0.842	0.567

different methods – which, in practice, amounts to choosing the "CER-Sum" method, which is why we report this method in the paper. With an average bandwidth of 6.5pp and linear MOV controls, it yields a coverage rate of 87.3% with an average length of the confidence interval of 0.300. With such a small bandwidth, the robust (quadratic) estimator performs worse than the linear estimator, yielding a lower coverage despite a much wider confidence interval. The MSE-based estimators for the simple RDD without interaction terms based on Calonico, Cattaneo and Titiunik (2014) pick a smaller average bandwidth than our MSE-based approach for the full model (2.2) with interactions. However, its average bandwidth, around 9pp, is higher than that of CER-based methods and its coverage slightly lower. We conclude that to have an estimator that accomplishes good coverage by "undersmoothing", the CER-Sum estimator with linear MOV controls is preferable.

In summary, we found that the nominal 90% confidence interval of our linear estimator with cross-validated bandwidth has a coverage of 82.1% – in a DGP modeled after our actual data. This size distortion is apparent, but more modest than some size distortions reported in Table 1 in Calonico, Cattaneo and Titiunik (2014) for the conventional approach in their "Model 2", for example. Both undersmoothing with the CER approach and the robust estimator with the cross-validated MSE bandwidth selection lead to a coverage of about 87%. While this coverage is still slightly below the nominal coverage, it is comparable to the performance of various robust estimators in Table 1 in Calonico, Cattaneo and Titiunik (2014), where the actual coverage can run more than 5pp below the nominal coverage. We conclude that our estimators have sound statistical properties in our setting.

B.2 Identification of the interaction term

Consider the following econometric model:

$$Y = \mu_y + \alpha X + \beta XD + \gamma D + \varepsilon, \qquad \varepsilon \sim iid(0,1) \tag{B.1}$$

$$X = \mu_x + \sigma_x(\sqrt{1-\rho^2}\nu + \rho\varepsilon) \qquad \nu \sim iid(0,1) \tag{B.2}$$

$$D \overset{iid}{\sim} \text{Bernoulli}(p), p \in (0,1). \tag{B.3}$$

Notice that this DGP satisfies $(X, \varepsilon) \perp\!\!\!\perp D$, but $\text{Corr}(X, \varepsilon) = \rho$, so that X is endogenous to shocks to Y.

Proposition 1. *Under regularity conditions, β is consistently estimated by OLS in population, but α is only consistently estimated in population if $\rho = 0$.*

Intuitively, to estimate β, we marginalize out X and D first. For simplicity, assume that $\mu_x = \mu_y = 0$. First, note that $\text{Cov}[XD, D] = \mathbb{E}[X]\,\text{Var}[D]$ under independence of D and X, which is zero when $\mathbb{E}[X] = \mu_x = 0$. To marginalize out X note that $\mathbb{E}[XD|X] = \frac{\text{Cov}[XD,X]}{\text{Var}[X]}X = \mathbb{E}[D]X$. The residualized $XD - \mathbb{E}[XD|X] = X(D - \mathbb{E}[D])$ has zero covariance with the error term in Y: $\mathbb{E}[\varepsilon(XD - \mathbb{E}[XD|X])] = \mathbb{E}[\varepsilon X(D - \mathbb{E}[D])]$, which, by the law of iterated expectations, equals $\mathbb{E}[\varepsilon X \mathbb{E}[D - \mathbb{E}[D]|X, \varepsilon]]$. But joint independence means that $\mathbb{E}[D - \mathbb{E}[D]|X, \varepsilon] = \mathbb{E}[D - \mathbb{E}[D]] = 0$, yielding a zero covariance with the error term. Mechanically, the residualized $X(D - \mathbb{E}[D])$ is also uncorrelated with X and D individually, and the OLS estimator in population is given by $\hat{\beta} \xrightarrow{p} \frac{\text{Cov}[X(D-\mathbb{E}[D]),Y]}{\text{Var}[X(D-\mathbb{E}[D])]} = \frac{\text{Cov}[X(D-\mathbb{E}[D]),\beta XD]}{\text{Var}[X(D-\mathbb{E}[D])]} = \beta$.

Below, we give a full proof for the general problem of estimating α and β jointly without restricting μ_x and μ_y, and we characterize the asymptotic bias in estimating α.

Proof. Let $\mathbf{x} = [X, XD, D]$. Using the Frisch-Waugh Theorem, we can write the OLS estimator as

$$\begin{bmatrix} \hat{\alpha} \\ \hat{\beta} \\ \hat{\gamma} \end{bmatrix} = \widehat{\text{Cov}}[\mathbf{x}, \mathbf{x}]^{-1} \widehat{\text{Cov}}[\mathbf{x}, Y]. \tag{B.4}$$

Under regularity conditions, the estimated covariances converge to their population counterparts by a Law of Large Numbers. The OLS estimator is thus characterized by the entries of $\text{Cov}[\mathbf{x}, y]$ and $\text{Var}[\mathbf{x}]$, whose population counterparts we now compute.

We use repeatedly the following property:

$$\begin{aligned}
\mathbb{E}[f(X,\varepsilon)D] &= \mathbb{E}[\mathbb{E}[f(X,\varepsilon)D|X,\varepsilon]] && \text{law of iterated expectations} \\
&= \mathbb{E}[f(X,\varepsilon)\mathbb{E}[D|X,\varepsilon]] \\
&= \mathbb{E}[f(X,\varepsilon)\mathbb{E}[D]] && (X,\varepsilon) \perp\!\!\!\perp D \\
&= \mathbb{E}[f(X,\varepsilon)]\mathbb{E}[D].
\end{aligned} \tag{B.5}$$

We also use that $D^2 = D$.

As an intermediate step, compute the following variances and covariances:

$$\operatorname{Cov}[X,D] = \mathbb{E}[XD] - \mathbb{E}[X]\mathbb{E}[D] \overset{(B.5)}{=} \mathbb{E}[X]\mathbb{E}[D] - \mathbb{E}[X]\mathbb{E}[D] = 0 \tag{B.6a}$$

$$\operatorname{Cov}[X,XD] = \mathbb{E}[X^2D] - \mathbb{E}[X]\mathbb{E}[XD] \overset{(B.5)}{=} \mathbb{E}[X^2]\mathbb{E}[D] - \mathbb{E}[X]^2\mathbb{E}[D] = \operatorname{Var}[X]\mathbb{E}[D] \tag{B.6b}$$

$$\begin{aligned}\operatorname{Cov}[XD,D] &= \mathbb{E}[XD^2] - \mathbb{E}[XD]\mathbb{E}[D] \overset{D^2=D}{=} \mathbb{E}[XD] - \mathbb{E}[XD]\mathbb{E}[D] \\ &\overset{(B.5)}{=} \mathbb{E}[X]\mathbb{E}[D] - \mathbb{E}[X]\mathbb{E}[D]^2 = \mathbb{E}[X]\operatorname{Var}[D]\end{aligned} \tag{B.6c}$$

$$\begin{aligned}\operatorname{Var}[XD] &= \mathbb{E}[X^2D^2] - \mathbb{E}[XD]^2 \overset{D^2=D}{=} \mathbb{E}[X^2D] - \mathbb{E}[XD]^2 \\ &\overset{(B.5)}{=} \mathbb{E}[X^2]\mathbb{E}[D] - \mathbb{E}[X]^2\mathbb{E}[D]^2 = \operatorname{Var}[X]\mathbb{E}[D] + \mathbb{E}[X]^2(\mathbb{E}[D] - \mathbb{E}[D]^2 \\ &= \operatorname{Var}[X]\mathbb{E}[D] + \mathbb{E}[X]^2\operatorname{Var}[D]\end{aligned} \tag{B.6d}$$

$$\operatorname{Cov}[X,\varepsilon] = \mathbb{E}[X\varepsilon] - \mathbb{E}[X]\mathbb{E}[\varepsilon] \overset{\mathbb{E}[\varepsilon]=0}{=} \mathbb{E}[X\varepsilon] \overset{\mathbb{E}[\varepsilon]=\mathbb{E}[u\varepsilon]=0}{=} \rho\sigma_x \tag{B.6e}$$

$$\begin{aligned}\operatorname{Cov}[XD,\varepsilon] &= \mathbb{E}[XD\varepsilon] - \mathbb{E}[XD]\mathbb{E}[\varepsilon] \overset{\mathbb{E}[\varepsilon]=0}{=} \mathbb{E}[XD\varepsilon] \overset{(B.5)}{=} \mathbb{E}[X\varepsilon]\mathbb{E}[D] \\ &\overset{\mathbb{E}[\varepsilon]=\mathbb{E}[u\varepsilon]=0}{=} \rho\sigma_x\mathbb{E}[D]\end{aligned} \tag{B.6f}$$

$$\operatorname{Cov}[D,\varepsilon] = \mathbb{E}[D\varepsilon] - \mathbb{E}[D]\mathbb{E}[\varepsilon] \overset{(B.5)}{=} \mathbb{E}[\varepsilon]\mathbb{E}[D] - \mathbb{E}[D]\mathbb{E}[\varepsilon] = 0 \tag{B.6g}$$

We can now express the two factors of the OLS estimator

$$\begin{aligned}\operatorname{Var}[\mathbf{x}]^{-1} &= \begin{bmatrix}\operatorname{Var}[X] & & \\ \operatorname{Cov}[X,XD] & \operatorname{Var}[XD] & \\ \operatorname{Cov}[X,D] & \operatorname{Cov}[XD,D] & \operatorname{Var}[D]\end{bmatrix}^{-1} = \begin{bmatrix}\operatorname{Var}[X] & & \\ \operatorname{Cov}[X,XD] & \operatorname{Var}[XD] & \\ 0 & \operatorname{Cov}[XD,D] & \operatorname{Var}[D]\end{bmatrix}^{-1} \\ &= \frac{1}{\det}\begin{bmatrix}\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2 & & \\ -\operatorname{Var}[D]\operatorname{Cov}[XD,X] & \operatorname{Var}[D]\operatorname{Var}[X] & \\ \operatorname{Cov}[XD,D]\operatorname{Cov}[XD,X] & -\operatorname{Cov}[XD,D]\operatorname{Var}[X] & \operatorname{Var}[X]\operatorname{Var}[XD] - \operatorname{Cov}[XD,X]^2\end{bmatrix} \\ \det &= \operatorname{Var}[X]\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2\operatorname{Var}[X] - \operatorname{Cov}[XD,X]^2\operatorname{Var}[D]\end{aligned} \tag{B.7}$$

and

$$\begin{aligned}\operatorname{Cov}[\mathbf{x},Y] &= \begin{bmatrix}\alpha\operatorname{Var}[X] + \beta\operatorname{Cov}[X,XD] + \gamma\operatorname{Cov}[X,D] + \operatorname{Cov}[X,\varepsilon] \\ \alpha\operatorname{Cov}[X,XD] + \beta\operatorname{Var}[XD] + \gamma\operatorname{Cov}[XD,D] + \operatorname{Cov}[XD,\varepsilon] \\ \alpha\operatorname{Cov}[X,D] + \beta\operatorname{Cov}[XD,D] + \gamma\operatorname{Var}[D] + \operatorname{Cov}[D,\varepsilon]\end{bmatrix} \\ &= \begin{bmatrix}\alpha\operatorname{Var}[X] + \beta\operatorname{Cov}[X,XD] + \operatorname{Cov}[X,\varepsilon] \\ \alpha\operatorname{Cov}[X,XD] + \beta\operatorname{Var}[XD] + \gamma\operatorname{Cov}[XD,D] + \operatorname{Cov}[XD,\varepsilon] \\ \beta\operatorname{Cov}[XD,D] + \gamma\operatorname{Var}[D]\end{bmatrix}\end{aligned} \tag{B.8}$$

Now, the limit for the OLS estimator of interest, $\hat{\beta}$ in population, is given by:

$$\begin{aligned}\hat{\beta} &\xrightarrow{p} \begin{bmatrix}0 & 1 & 0\end{bmatrix}\operatorname{Var}[\mathbf{x}]^{-1}\operatorname{Cov}[\mathbf{x},Y] \\ &= \frac{1}{\det}\begin{pmatrix}-\operatorname{Cov}[XD,X]\operatorname{Var}[D](\alpha\operatorname{Var}[X] + \beta\operatorname{Cov}[X,XD] + \operatorname{Cov}[X,\varepsilon]) \\ +\operatorname{Var}[D]\operatorname{Var}[X](\alpha\operatorname{Cov}[X,XD] + \beta\operatorname{Var}[XD] + \gamma\operatorname{Cov}[XD,D] + \operatorname{Cov}[XD,\varepsilon]) \\ -\operatorname{Cov}[XD,D]\operatorname{Var}[X](\beta\operatorname{Cov}[XD,D] + \gamma\operatorname{Var}[D])\end{pmatrix}\end{aligned}$$

$$= \frac{1}{\det}\begin{pmatrix} \alpha(\operatorname{Var}[D]\operatorname{Var}[X]\operatorname{Cov}[X,XD] - \operatorname{Cov}[XD,X]\operatorname{Var}[D]\operatorname{Var}[X]) \\ +\beta(\operatorname{Var}[D]\operatorname{Var}[X]\operatorname{Var}[XD] - \operatorname{Cov}[XD,X]^2\operatorname{Var}[D] - \operatorname{Cov}[XD,D]^2\operatorname{Var}[X]) \\ +\gamma(\operatorname{Var}[D]\operatorname{Var}[X]\operatorname{Cov}[XD,D] - \operatorname{Cov}[XD,D]\operatorname{Var}[X]\operatorname{Var}[D]) \\ +\operatorname{Var}[D]\operatorname{Var}[X]\operatorname{Cov}[XD,\varepsilon]) - \operatorname{Cov}[XD,X]\operatorname{Var}[D]\operatorname{Cov}[X,\varepsilon] \end{pmatrix}$$

$$= \frac{1}{\det}\begin{pmatrix} +\beta\det \\ +\operatorname{Var}[D]\operatorname{Var}[X]\mathbb{E}[D]\operatorname{Cov}[X,\varepsilon] - \mathbb{E}[D]\operatorname{Var}[X]\operatorname{Var}[D]\operatorname{Cov}[X,\varepsilon] \end{pmatrix} = \beta \tag{B.9}$$

Thus, the interaction term is consistently estimated.

Now, the limit for the coefficient on X itself, $\hat{\alpha}$ in population, is given by:

$$\begin{aligned} \hat{\alpha} &\xrightarrow{p} \begin{bmatrix}1 & 0 & 0\end{bmatrix}\operatorname{Var}[\mathbf{x}]^{-1}\operatorname{Cov}[\mathbf{x},Y] \\ &= \frac{1}{\det}\begin{pmatrix} (\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2)(\alpha\operatorname{Var}[X] + \beta\operatorname{Cov}[X,XD] + \operatorname{Cov}[X,\varepsilon]) \\ -\operatorname{Var}[D]\operatorname{Cov}[XD,X](\alpha\operatorname{Cov}[X,XD] + \beta\operatorname{Var}[XD] + \gamma\operatorname{Cov}[XD,D] + \operatorname{Cov}[XD,\varepsilon]) \\ +\operatorname{Cov}[XD,D]\operatorname{Cov}[XD,X](\beta\operatorname{Cov}[XD,D] + \gamma\operatorname{Var}[D]) \end{pmatrix} \\ &= \frac{1}{\det}\begin{pmatrix} \alpha(\operatorname{Var}[D]\operatorname{Var}[X]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2\operatorname{Var}[X] - \operatorname{Var}[D]\operatorname{Cov}[XD,X]^2) \\ +\beta(\operatorname{Var}[D]\operatorname{Var}[XD]\operatorname{Cov}[XD,X] - \operatorname{Cov}[XD,D]^2\operatorname{Cov}[XD,X]) \\ +\beta(-\operatorname{Cov}[XD,X]\operatorname{Var}[XD]\operatorname{Var}[D] + \operatorname{Cov}[XD,D]^2\operatorname{Cov}[XD,X]) \\ +\gamma(\operatorname{Var}[D]\operatorname{Cov}[XD,X]\operatorname{Cov}[XD,D] - \operatorname{Cov}[XD,D]\operatorname{Cov}[XD,X]\operatorname{Var}[D]) \\ +(\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2)\operatorname{Cov}[X,\varepsilon] - \operatorname{Var}[D]\operatorname{Cov}[XD,X]\operatorname{Cov}[XD,\varepsilon]) \end{pmatrix} \\ &= \alpha + \frac{(\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2)\operatorname{Cov}[X,\varepsilon] - \operatorname{Var}[D]\operatorname{Cov}[XD,X]\operatorname{Cov}[XD,\varepsilon]}{\det} \end{aligned} \tag{B.10}$$

Note that:

$$\begin{aligned} &(\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2)\operatorname{Cov}[X,\varepsilon] - \operatorname{Var}[D]\operatorname{Cov}[XD,X]\operatorname{Cov}[XD,\varepsilon] \\ &= (\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2)\operatorname{Cov}[X,\varepsilon] - \operatorname{Var}[D]\operatorname{Cov}[XD,X]\mathbb{E}[D]\operatorname{Cov}[X,\varepsilon] \\ &= \operatorname{Cov}[X,\varepsilon]\left(\operatorname{Var}[D]\operatorname{Var}[XD] - \operatorname{Cov}[XD,D]^2 - \operatorname{Var}[D]\operatorname{Cov}[XD,X]\mathbb{E}[D]\right) \\ &= \operatorname{Cov}[X,\varepsilon]\left(\operatorname{Var}[D](\mathbb{E}[X^2]\mathbb{E}[D] - \mathbb{E}[X]^2\mathbb{E}[D]^2) - \mathbb{E}[X]^2\operatorname{Var}[D]^2 - \operatorname{Var}[D]\mathbb{E}[D]^2\operatorname{Var}[X]\right) \\ &= \operatorname{Cov}[X,\varepsilon]\operatorname{Var}[D]\left(\mathbb{E}[X^2]\mathbb{E}[D] - \mathbb{E}[X]^2\mathbb{E}[D]^2 - \mathbb{E}[X]^2\operatorname{Var}[D] - \mathbb{E}[D]^2\operatorname{Var}[X]\right) \\ &= \operatorname{Cov}[X,\varepsilon]\operatorname{Var}[D]\left(\mathbb{E}[X^2]\mathbb{E}[D] - \mathbb{E}[X]^2\mathbb{E}[D]^2 - \mathbb{E}[X]^2(\mathbb{E}[D] - \mathbb{E}[D]^2) - \mathbb{E}[D]^2\operatorname{Var}[X]\right) \\ &= \operatorname{Cov}[X,\varepsilon]\operatorname{Var}[D]\left(\mathbb{E}[X^2]\mathbb{E}[D] - \mathbb{E}[X]^2\mathbb{E}[D] - \mathbb{E}[D]^2\operatorname{Var}[X]\right) \\ &= \operatorname{Cov}[X,\varepsilon]\operatorname{Var}[D]\left(\operatorname{Var}[X]\mathbb{E}[D] - \mathbb{E}[D]^2\operatorname{Var}[X]\right) = \operatorname{Cov}[X,\varepsilon]\operatorname{Var}[D]\operatorname{Var}[X]\mathbb{E}[D]\,(1 - \mathbb{E}[D]) \\ &\propto \operatorname{Cov}[X,\varepsilon]. \end{aligned} \tag{B.11}$$

which, for $p \in (0,1)$ is, only zero if $\rho = 0$ and X is exogenous. Thus, the baseline coefficient is not consistently estimated. □

C Additional Tables

In this Appendix section, we present robustness results referenced in our main text. Each subsection is organized to a point in our text.

C.1 Local randomization approach

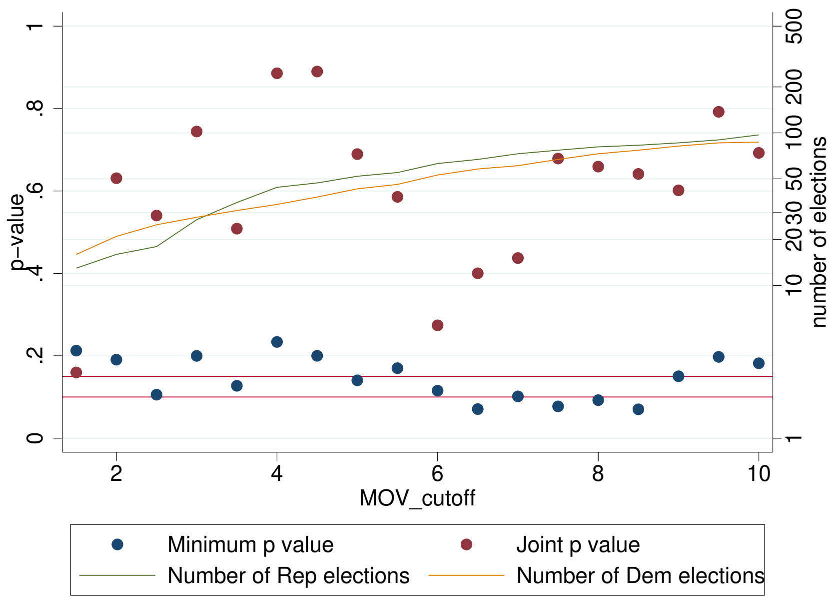
To implement the local randomization approach to the RDD, we follow Cattaneo, Idrobo and Titiunik (2018) and choose a bandwidth for the MOV in which we cannot reject that the close election sample is a balanced experiment according to a number of covariates. Specifically, we consider bandwidths for which we have at least 10 elections on either side of the cutoff, in practice a MOV of at least 1.5pp, and then test for equality of the covariates listed below on each side of the cutoff. We pick the largest bandwidth before the minimum p-value across covariates drops below .15. We cluster standard errors by election.

We use a "kitchen sink" of covariates. Given the importance of our assumption that IG growth is exogenous on both sides of the cutoff, we choose six variables concerning current IG growth and two variables concerning previous term IG growth. Other variables concern predetermined quantities characterizing politics and the economy:

1. IG growth excluding welfare aid
2. IG growth excluding welfare aid, positive only
3. IG growth excluding welfare aid, cuts only
4. IG growth excluding welfare aid and highway aid
5. IG growth excluding welfare aid and highway aid, positive only
6. IG growth excluding welfare aid and highway aid, cuts only
7. Average previous term expenditure growth
8. Average previous term IG growth
9. Average previous term IG growth excluding welfare aid
10. Lagged share of Democrats in the legislature
11. Average previous term population growth
12. Average previous IG share in total revenue
13. Average previous term general revenue to GDP
14. Average previous term debt level
15. Average previous term GDP level
16. Average previous term GDP growth

Figure C.1.1 shows the results. For an MOV below 2pp in absolute terms, the minimum p-value is about 0.2. At a MOV of 2.5pp it drops to just above .1, so we select 2pp as our bandwidth. At that bandwidth, we have just below 40 elections, with slightly fewer Republican than Democratic governors in our sample.

Figure C.1.1: Graph Illustrating Bandwidth Selection for Local RDD



C.2 Alternative estimators

The literature proposes several different RDD estimators. In the main paper, we use the frontier estimator proposed by Calonico, Cattaneo and Titiunik (2014). In this subsection, we consider two different other estimators:

- **Alternative estimator 1: Linear CER (undersmoothing)**: Since the possible bias originates from an overly large bandwidth, we also choose a bandwidth for a standard, linear RDD without interactions that minimizes the "coverage-error-rate," called the linear CER estimator. The linear CER trades off error variance against bias, rather than the squared bias. Because it is applied to a model without interaction terms, it typically yields a smaller bandwidth $\bar{m}$. Simulations show that confidence intervals based on either the robust estimator or the linear CER estimator have good coverage. We thank an anonymous referee for suggesting this approach based on undersmoothing. See Methodological Appendix B.1 for the Monte Carlo study of estimators.
- **Alternative estimator 2: Local RDD** We also consider a local randomization approach that uses covariate balance as a criterion to calibrate a bandwidth that is small enough to plausibly assume there is no need for MOV controls (Cattaneo, Idrobo and Titiunik, 2018). We denote this estimator as "Local." We provide detail on the methodology in Online Appendix C.1.

Table 2 shows our alternative RDD estimators as a modified version of Table C.2.1. Columns (1), (2), (5), and (6) of Table C.2.1 are identical to results in the main text. Columns (3) and (7) provide estimates for the model with linear MOV controls but with a bandwidth calibrated to minimize the CER for an RDD without IG terms. Column (4) presents estimates for the local randomization RDD using OLS without MOV controls and a bandwidth of MOV$\leq$2pp.[4] In this table, we see that the estimates for our parameter of interest are similar to those in the paper, despite using different estimators.

[4] See Appendix C.1 for a description of the bandwidth selection procedure.

Table C.2.1: MPS Elasticity Estimates: IG Aid Excluding Welfare Aid

	Without fixed effects				With fixed effects		
	(1) Linear MSE	(2) Robust	(3) Lin CER	(4) OLS	(5) Linear MSE	(6) Robust	(7) OLS
Pos IG growth	0.203	0.134	0.213	0.104	0.180	0.119	0.221
	(0.077)	(0.109)	(0.123)	(0.041)	(0.043)	(0.077)	(0.075)
Rep gov x Pos IG growth	-0.260	-0.327	-0.348	-0.193	-0.272	-0.290	-0.408
	(0.104)	(0.130)	(0.126)	(0.084)	(0.075)	(0.098)	(0.105)
Neg IG growth	0.199	0.132	0.161	0.144	-0.016	-0.069	-0.041
	(0.067)	(0.102)	(0.088)	(0.074)	(0.067)	(0.123)	(0.108)
Rep gov x Neg IG growth	0.187	0.442	0.297	0.442	0.332	0.524	0.407
	(0.080)	(0.200)	(0.129)	(0.145)	(0.099)	(0.239)	(0.159)
Rep gov	0.022	0.039	0.033	0.031			
	(0.005)	(0.010)	(0.008)	(0.007)			
R-squared	0.18	0.19	0.20	0.27	0.54	0.54	0.57
R-sq, within	0.18	0.19	0.20	0.27	0.11	0.12	0.12
Observations	678	678	458	123	630	630	457
States	48	48	46	27	47	47	46
Years	32	32	32	32	32	32	32
State FE	None	None	None	None	By party	By party	By party
Year FE	None	None	None	None	By party	By party	By party
MOV bandwidth (pp)	11.0	11.0	7.1	2.0	10.0	10.0	7.1

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

C.3 Pre-trends

The final column of Table 1 reported the results of tests for equality of means in the group of exogenous variables. These tests allow us to assess the internal validity of our RDD. None of the tests for the equality of the sample means are statistically different from zero at the 90 percent confidence interval ($t > 1.65$). Still, a concern is that while the sample means for prior term expenditure growth are identical at 2.9%, the robust t-statistic for the difference in means is relatively high at 1.4 but statistically insignificant. To make sure that the MPS estimates reported in Table 2 are not driven by prior term expenditure growth, or other pre-trends, we include interaction terms for several prior trends in Equation C.1:

$$\begin{aligned}\Delta \ln E_{s,t} =& \mu_0 + \mu_r \times Rep_{s,t-1} + \sum_{\mathfrak{s}\in\{cut,inc\}} (\gamma_{0,\mathfrak{s}} + \gamma_{r,\mathfrak{s}} \times Rep_{s,t-1}) \Delta \ln IG^{\mathfrak{s}}_{s,t}) \\ & + (IA_{s,t-1} - \overline{IA}_{s,t-1}) \times \Big(\theta_0 + \theta_r \times Rep_{s,t-1} + \\ & \sum_{\mathfrak{s}\in\{cut,inc\}} (\gamma_{0,\mathfrak{s},IA} + \gamma_{r,\mathfrak{s},IA} \times Rep_{s,t-1}) \Delta \ln IG^{\mathfrak{s}}_{s,t}\Big) \\ & + (\text{MOV}, \text{MOV}^2) \times \text{IG} \times \text{demeaned IA} \times \text{party interactions } + e_{s,t}. \end{aligned} \tag{C.1}$$

Three alternative interaction terms, denoted IA, are alternatively included when estimating Equation (C.1): prior term expenditure growth, prior term overall IG growth, and prior term IG growth excluding welfare. As in the paper, changes in log expenditures are denoted $\ln(E_{s.t})$, in state s in fiscal year t in response to changes in $\ln(IG_{s,t})$. The effect of aid may differ when aid increases ($\Delta ln(IG^{+}_{s,t}) = \max\{0, \Delta ln(IG_{s,t})\}$) or decreases ($\Delta \ln(IG^{-}_{s,t}) = \min\{0, \Delta \ln(IG_{s,t})\}$), and by party of governor denoted as Republican ($Reps_{t-1} = 1$) or Democratic ($Reps_{t-1} = 0$).

Table C.3.1 reports the findings. The results reported in Table C.3.1 are highly robust to those reported in Table 2. For example, the finding reported in Column (2) of Table C.3.1 that Republican governors spend 0.320pp less of a 1% increase in IG aid compared with their Democratic counterparts is almost identical to the 0.327pp difference reported in Column (2) of Table 2. In general, Table C.3.1 verifies that the results reported in Table 2 are not driven by prior term expenditure growth, or other pre-trends.

Table C.3.1: Partisan Determinants of Expenditure Growth: Prior Term Interactions, 1983 to 2014, with Fixed Effects.

Interaction variable (IA) =	Prior term exp growth		Prior term overall IG growth	
	(1) Lin CV	(2) Robust CV	(3) Lin CV	(4) Robust CV
Pos IG growth	0.188	0.092	0.166	0.164
	(0.05)	(0.09)	(0.04)	(0.07)
pos IG x IA	0.004	-0.026	-0.015	-0.020
	(0.04)	(0.06)	(0.02)	(0.03)
Rep gov x Pos IG growth	-0.315	-0.320	-0.246	-0.443
	(0.09)	(0.14)	(0.09)	(0.11)
pos IG x Rep gov x IA	-0.038	-0.047	-0.031	-0.034
	(0.05)	(0.07)	(0.02)	(0.03)
Neg IG growth	-0.038	-0.049	0.021	-0.115
	(0.08)	(0.18)	(0.05)	(0.13)
neg IG x IA	0.006	-0.030	-0.004	0.012
	(0.03)	(0.06)	(0.01)	(0.02)
Rep gov x Neg IG growth	0.388	0.436	0.288	0.440
	(0.13)	(0.28)	(0.09)	(0.25)
neg IG x Rep gov x IA	0.009	0.188	0.026	0.025
	(0.04)	(0.08)	(0.01)	(0.03)
R-squared	0.54	0.56	0.54	0.55
R-sq, within	0.12	0.15	0.12	0.13
Observations	630	630	676	676
States	47	47	48	48
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	10.0	10.0	11.0	11.0

Notes: Estimated MOV polynomials and their IA interactions not shown. Standard errors clustered by state and year.

C.4 Level Robustness

In Tables C.4.1 and Tables C.4.2, we show the full array of RDD specifications for level estimates beyond what we show in Table 4. In Table C.4.1, we show our estimates without fixed effects and, in Table C.4.2 with fixed effects. Table C.4.1 shows different RDD estimators for the impact of $\Delta IG_{s,t}$ on $\frac{E_{s,t-1}}{IG_{s,t-1}}\Delta \ln E_{s,t}$ and Table C.4.3 reports the results of a dollar-on-dollar regression for various specifications

In Table 4, we see that the magnitude of the partisan difference estimate remains relatively similar with the inclusion and exclusion of fixed effects; however, the inclusion of fixed estimates makes the estimates more precise. In Tables C.4.3 and C.4.4, we see that our results are similar to the alternative specification.

Table C.4.1: MPS Dollar Estimates for Non-Welfare IG Transfers: 1983-2014

	Without fixed effects			
	(1) Lin CV	(2) Robust CV	(3) Lin CER-Sum	(4) OLS
Pos IG growth	1.483	1.337	1.198	1.414
	(0.396)	(0.626)	(0.931)	(0.195)
Rep gov x Pos IG growth	-1.184	-1.683	-1.712	-0.869
	(0.570)	(1.013)	(1.235)	(0.208)
Neg IG growth	0.981	1.286	1.574	0.982
	(0.436)	(0.695)	(0.774)	(0.312)
Rep gov x Neg IG growth	1.769	2.062	2.401	1.122
	(0.530)	(0.896)	(1.762)	(0.242)
R-squared	0.17	0.18	0.20	0.14
R-sq, within	0.17	0.18	0.20	0.14
Observations	1047	1047	400	1508
States	48	48	46	48
Years	32	32	32	32
State FE	None	None	None	None
Year FE	None	None	None	None
MOV bandwidth (pp)	21.0	21.0	6.1	

Standard errors clustered by state and year in parentheses.

Table C.4.2: MPS Dollar Estimates for Non-Welfare IG Transfers: 1983-2014

	With fixed effects			
	(1) Lin CV	(2) Robust CV	(3) Lin CER-Sum	(4) OLS
Pos IG growth	1.285	1.346	1.594	1.276
	(0.356)	(0.600)	(0.700)	(0.186)
Rep gov x Pos IG growth	-0.944	-1.576	-2.562	-0.702
	(0.517)	(0.892)	(1.398)	(0.181)
Neg IG growth	0.135	0.332	-0.771	0.073
	(0.367)	(0.805)	(1.309)	(0.141)
Rep gov x Neg IG growth	1.785	2.831	4.830	1.096
	(0.627)	(1.105)	(2.177)	(0.159)
R-squared	0.46	0.47	0.60	0.41
R-sq, within	0.09	0.09	0.16	0.07
Observations	1070	1070	396	1508
States	48	48	46	48
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	22.0	22.0	6.1	

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.4.3: MPS Dollar Estimates for Non-Welfare IG Transfers: 1983-2014, Level estimation without fixed effects.

	Without fixed effects			
	(1) Lin CV	(2) Robust CV	(3) Lin CER-Sum	(4) OLS
Pos IG growth	1.281	0.779	1.293	1.275
	(0.427)	(0.965)	(1.033)	(0.110)
Rep gov x Pos IG growth	-1.473	-2.084	-2.042	-0.634
	(0.742)	(1.238)	(1.112)	(0.180)
Neg IG growth	1.518	1.192	1.318	1.085
	(0.407)	(0.760)	(0.563)	(0.293)
Rep gov x Neg IG growth	1.487	2.764	1.978	0.371
	(0.615)	(1.577)	(1.151)	(0.298)
R-squared	0.24	0.25	0.24	0.18
R-sq, within	0.24	0.25	0.24	0.18
Observations	678	678	441	1508
States	48	48	46	48
Years	32	32	32	32
State FE	None	None	None	None
Year FE	None	None	None	None
MOV bandwidth (pp)	11.0	11.0	6.6	

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.4.4: MPS Dollar Estimates for Non-Welfare IG Transfers: 1983-2014, Level estimation with fixed effects.

	With fixed effects			
	(1) Lin CV	(2) Robust CV	(3) Lin CER-Sum	(4) OLS
Pos IG growth	0.779	0.870	1.114	1.091
	(0.346)	(0.546)	(0.664)	(0.205)
Rep gov x Pos IG growth	-1.449	-2.495	-3.342	-0.570
	(0.881)	(1.156)	(1.178)	(0.202)
Neg IG growth	0.523	0.256	0.030	0.265
	(0.216)	(0.558)	(0.642)	(0.151)
Rep gov x Neg IG growth	2.307	2.203	3.065	0.713
	(0.505)	(1.594)	(1.420)	(0.175)
R-squared	0.54	0.54	0.59	0.43
R-sq, within	0.12	0.12	0.13	0.09
Observations	703	703	439	1508
States	48	48	46	48
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	12.0	12.0	6.6	

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

C.5 External Validity: Ideology

We consider whether candidate ideological scores could affect the estimated size of the coefficients measuring partisan differences ($\gamma_{r,inc}, \gamma_{r,cut}$). To address this issue, we test whether candidate ideological scores interacted with partisan differences affect the estimated size of the coefficients measuring partisan differences.

Let IA denote the campaign finance (CF) score of Republican and Democratic candidates. As in the paper, changes in log expenditures are denoted $\ln(E_{s.t})$, in state s in fiscal year t in response to changes in $ln(IG_{s,t})$. The effect of aid may differ when aid increases ($\Delta ln(IG^{+}_{s,t}) = \max\{0, \Delta ln(IG_{s,t})\}$) or decreases ($\Delta \ln(IG^{-}_{s,t}) = \min\{0, \Delta \ln(IG_{s,t})\}$), and by party of governor denoted as Republican ($Reps_{t-1} = 1$) or Democratic ($Reps_{t-1} = 0$).

$$\begin{aligned}\Delta \ln E_{s,t} = &\mu_0 + \mu_r \times Rep_{s,t-1} + \sum_{\mathfrak{s}\in\{cut,inc\}} (\gamma_{0,\mathfrak{s}} + \gamma_{r,\mathfrak{s}} \times Rep_{s,t-1})\Delta \ln IG^{\mathfrak{s}}_{s,t}) \\ &+ (IA_{s,t-1} - \overline{IA}_{s,t-1}) \times \Big(\theta_0 + \theta_r \times Rep_{s,t-1} + \\ &\sum_{\mathfrak{s}\in\{cut,inc\}} (\gamma_{0,\mathfrak{s},IA} + \gamma_{r,\mathfrak{s},IA} \times Rep_{s,t-1})\Delta \ln IG^{\mathfrak{s}}_{s,t}\Big) \\ &+ (\text{MOV, MOV}^2) \times \text{IG} \times \text{demeaned IA} \times \text{party interactions } + e_{s,t}. \end{aligned} \quad \text{(C.2)}$$

We consider two possible ideology concerns. In the first two columns of Table C.5.1, we allow for the possibility of time-varying ideology scores. In the final two columns of Table C.5.1 we consider measures of average state-level average ideology scores to rule out state-specific ideological concerns. Table C.5.1 shows the results from estimating Equation C.2. For the robust estimator we found no significant interaction effects interacted with partisan differences for either time-varying ideology or the average ideology versions of the regressions.

Table C.5.1: MPS Elasticity Estimates and Ideology Interactions: 1983–2014
We consider two possible ideology concerns. First, we allow for time-varying ideology based on candidates in the first two columns. Second, we consider measures of state-level average ideology to rule out specific ideological concerns.

	Time-varying ideology with first value cast backward		Average ideology by state	
	(1) Lin CV	(2) Robust CV	(3) Lin CV	(4) Robust CV
Pos IG growth	0.236	0.227	0.251	0.193
	(0.06)	(0.15)	(0.06)	(0.14)
pos IG x IA	-0.327	-0.035	-0.365	0.085
	(0.14)	(0.25)	(0.14)	(0.23)
Rep gov x Pos IG growth	-0.392	-0.410	-0.400	-0.356
	(0.10)	(0.18)	(0.10)	(0.16)
pos IG x Rep gov x IA	0.400	0.281	0.481	0.299
	(0.24)	(0.33)	(0.21)	(0.31)
Neg IG growth	-0.097	-0.202	-0.055	-0.130
	(0.07)	(0.20)	(0.07)	(0.16)
neg IG x IA	0.121	0.206	0.080	0.096
	(0.11)	(0.24)	(0.09)	(0.21)
Rep gov x Neg IG growth	0.483	0.593	0.423	0.476
	(0.12)	(0.27)	(0.13)	(0.28)
neg IG x Rep gov x IA	-0.175	-0.971	0.002	-0.637
	(0.31)	(0.58)	(0.23)	(0.45)
R-squared	0.58	0.59	0.58	0.59
R-sq, within	0.16	0.18	0.14	0.16
Observations	569	569	576	576
States	47	47	47	47
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party

Notes: Estimated MOV polynomials and their IA interactions not shown. Standard errors clustered by state and year.

C.6 Time-Series of Polarization

In the paper we asked: "Does the trend in polarization affect our estimates of a partisan difference in state policies?" To answer the question, we use the time series measure (1964-2014) of polarization from Azzimonti (2018), which is based on national news coverage of divided government. The Azzimonti measure of polarization has increased over time. We interact the Azzimonti series with dummy variables for Republican governors. An expenditure growth equation is estimated for the period 1983 to 2014.

In this specification, we note two core results: the second row of Table C.6.1 shows a negative and significant coefficient for the interaction term of the Republican governor and positive IG growth. This coefficient is in line with our baseline results. However, we find evidence that the partisan differences in the pass-through are larger in more polarized times given the sign and significance on the triple interaction in row 4 of Table C.6.1.

Table C.6.1: Partisan Determinants of Expenditure Growth: Azzimonti (2018) Interaction, 1983 to 2014, with Fixed Effects

	Linear MSE	Robust	Linear CER	OLS
Pos IG growth	0.177	0.195	0.162	0.154
	(0.03)	(0.05)	(0.07)	(0.02)
Rep gov x Pos IG growth	-0.097	-0.147	-0.210	-0.058
	(0.03)	(0.07)	(0.09)	(0.02)
pos IG x IA	-0.005	0.019	-0.010	-0.021
	(0.03)	(0.05)	(0.06)	(0.03)
pos IG x Rep gov x IA	-0.086	-0.130	-0.146	-0.058
	(0.04)	(0.06)	(0.08)	(0.03)
Neg IG growth	0.030	-0.007	0.028	0.047
	(0.02)	(0.04)	(0.05)	(0.02)
Rep gov x Neg IG growth	0.097	0.170	0.280	0.075
	(0.03)	(0.07)	(0.12)	(0.03)
neg IG x IA	-0.008	-0.008	0.004	-0.008
	(0.03)	(0.04)	(0.03)	(0.03)
neg IG x Rep gov x IA	0.035	0.043	-0.012	0.034
	(0.04)	(0.06)	(0.09)	(0.04)
R-squared	0.47	0.47	0.57	0.47
R-sq, within	0.11	0.12	0.14	0.11
Observations	2339	2339	861	2425
States	50	50	49	50
Years	51	51	51	51

Notes: IA = Historical Partisan Conflict. Estimated MOV polynomials and their IA interactions not shown. Standard errors clustered by state and year.

C.7 Partisan Determinants of Tax and Debt Changes

This section provides the corresponding regressions supporting the graphs shown in Figure 6 in the paper of partisan interactions for the response of state-level debt to increased aid (Tables C.7.1 and C.7.2) and the response of marginal tax rates to increased IG aid (Tables C.7.3 and C.7.4). Given that states might not immediately choose to change either outstanding debt or tax rates, we consider the pass-through both in the current year, and up to three years out. For a 1pp increase in IG aid, total debt outstanding falls by 0.28pp more under Republican governors than under Democratic governors. There is some evidence that debt reduction is also present after three years.

Tables C.7.3 and C.7.4 show that on impact, there are no partisan differences in states' top marginal income tax rates. But after two years, for each 1pp increase in IG growth, the tax rate in Republican states is about 1%, or 0.05pp lower than that in Democratic states (this is not statistically significant). This outcome aligns well with the real-world institutional details of state-government: lengthy budget negotiations might result in delayed and lumpy tax reforms, which makes immediate debt-relief easier.

Table C.7.1: Partisan Determinants of Total Debt Outstanding Changes: 1983 to 2014

	1-year change		2-year change	
	(1) Lin CV	(2) Robust CV	(3) Lin CV	(4) Robust CV
Pos IG growth	0.232	0.302	0.222	0.237
	(0.096)	(0.124)	(0.161)	(0.223)
Rep gov x Pos IG growth	-0.163	-0.281	-0.071	-0.001
	(0.109)	(0.138)	(0.162)	(0.288)
Neg IG growth	-0.169	-0.038	-0.147	-0.105
	(0.245)	(0.288)	(0.351)	(0.411)
Rep gov x Neg IG growth	0.170	-0.116	0.242	0.012
	(0.268)	(0.333)	(0.378)	(0.461)
R-squared	0.34	0.35	0.42	0.43
R-sq, within	0.01	0.02	0.01	0.01
Observations	1104	1104	1070	1070
States	48	48	48	48
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	24.0	24.0	22.0	22.0

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.7.2: Partisan Determinants of Total Debt Outstanding Changes: 1983 to 2014.

	3-year change		4-year change	
	(5) Lin CV	(6) Robust CV	(7) Lin CV	(8) Robust CV
Pos IG growth	0.348	0.509	1.870	1.703
	(0.162)	(0.284)	(0.952)	(0.566)
Rep gov x Pos IG growth	-0.340	-0.316	-1.682	-1.116
	(0.177)	(0.354)	(0.994)	(0.509)
Neg IG growth	-0.530	-0.693	-3.845	-5.046
	(0.283)	(0.454)	(1.539)	(2.733)
Rep gov x Neg IG growth	0.880	0.864	4.264	5.526
	(0.332)	(0.514)	(1.669)	(3.218)
R-squared	0.49	0.49	0.74	0.74
R-sq, within	0.02	0.03	0.09	0.11
Observations	1036	1036	287	287
States	48	48	42	42
Years	31	31	30	30
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	22.0	22.0	5.0	5.0

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.7.3: Partisan Determinants of State Maximal Marginal Tax Rate Changes: 1983 to 2014 (1-year and 2-year change)

	1-year change		2-year change	
	(1) Lin CV	(2) Robust CV	(3) Lin CV	(4) Robust CV
Pos IG growth	-1.384	-1.112	0.287	0.696
	(1.819)	(1.228)	(1.563)	(2.944)
Rep gov x Pos IG growth	0.533	1.065	-1.342	-1.198
	(2.001)	(1.757)	(1.972)	(2.800)
Neg IG growth	2.746	4.783	0.481	0.753
	(2.760)	(2.277)	(2.557)	(2.169)
Rep gov x Neg IG growth	-1.202	-2.586	2.556	3.324
	(3.514)	(3.646)	(2.848)	(2.471)
R-squared	0.47	0.48	0.53	0.53
R-sq, within	0.03	0.03	0.02	0.02
Observations	314	314	386	386
States	43	43	45	45
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	5.0	5.0	6.0	6.0

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.7.4: Partisan Determinants of State Maximal Marginal Tax Rate Changes: 1983 to 2014 (3-year and 4-year change)

	3-year change		4-year change	
	(5) Lin CV	(6) Robust CV	(7) Lin CV	(8) Robust CV
Pos IG growth	1.083	1.838	-0.601	-0.085
	(1.543)	(2.081)	(1.453)	(1.988)
Rep gov x Pos IG growth	-1.900	-4.528	0.321	-0.143
	(1.553)	(2.108)	(2.326)	(4.822)
Neg IG growth	1.906	-0.433	2.451	2.577
	(1.450)	(2.541)	(1.492)	(2.411)
Rep gov x Neg IG growth	0.266	4.467	0.592	1.716
	(1.472)	(4.198)	(2.104)	(4.480)
R-squared	0.44	0.45	0.49	0.49
R-sq, within	0.04	0.05	0.04	0.05
Observations	524	524	524	524
States	47	47	47	47
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	8.0	8.0	8.0	8.0

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

C.8 Expenditure Type

In this appendix, we consider whether Democratic and Republican governors differ in the composition of their spending of IG aid transfers from the federal government. We consider three separate categories of expenditure growth: capital spending, federal IG transfers to state government that are reallocated to local governments, and current expenditure. Together, these categories account for 83% of total expenditure. Tables C.8.1 and C.8.2 show that we find robust partisan difference in capital expenditure growth and for transfers to state and local governments. In Table C.8.3, we find suggestive evidence for current expenditures. In Table C.8.4 we look at whether state governments transfer aid to households and whether aid is also used to cover interest expenses. We found no partisan differences in either transfers to households or interest expenditures. We interpret the findings in Table C.8.4 to suggest that increased aid leads to increased government consumption.

Table C.8.1: Partisan Determinants of Expenditure Growth Components with Partisan Differences: 1983 to 2014

	Capital expenditure (average: 8% of total)		
	Linear CV	Robust CV	OLS
Pos IG growth	0.367	0.786	0.530
	(0.175)	(0.200)	(0.127)
Rep gov x Pos IG growth	-0.697	-1.179	-0.254
	(0.252)	(0.408)	(0.120)
Neg IG growth	0.329	0.298	0.048
	(0.372)	(0.614)	(0.121)
Rep gov x Neg IG growth	0.916	0.060	0.627
	(0.513)	(0.862)	(0.184)
R-squared	0.35	0.36	0.18
R-sq, within	0.10	0.11	0.06
Observations	576	576	1508
States	47	47	48
Years	32	32	32
State FE	By party	By party	By party
Year FE	By party	By party	By party
MOV bandwidth (pp)	9.0	9.0	

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.8.2: Partisan Determinants of Expenditure Growth Components with Partisan Differences: 1983 to 2014

	IG transfers to local governments (25%)		
	Linear CV	Robust CV	OLS
Pos IG growth	0.208	0.257	0.122
	(0.090)	(0.105)	(0.047)
Rep gov x Pos IG growth	-0.327	-0.455	-0.141
	(0.113)	(0.169)	(0.067)
Neg IG growth	0.000	0.124	0.021
	(0.076)	(0.218)	(0.044)
Rep gov x Neg IG growth	0.140	0.193	0.039
	(0.169)	(0.330)	(0.075)
R-squared	0.22	0.22	0.19
R-sq, within	0.02	0.02	0.01
Observations	1162	1162	1508
States	48	48	48
Years	32	32	32
State FE	By party	By party	By party
Year FE	By party	By party	By party
MOV bandwidth (pp)	26.0	26.0	

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.8.3: Partisan Determinants of Expenditure Growth Components with Partisan Differences: 1983 to 2014

	Current expenditures (50%)		
	Linear CV	Robust CV	OLS
Pos IG growth	0.121	0.095	0.091
	(0.082)	(0.108)	(0.031)
Rep gov x Pos IG growth	-0.137	-0.180	-0.035
	(0.101)	(0.141)	(0.015)
Neg IG growth	0.004	-0.168	0.045
	(0.082)	(0.130)	(0.031)
Rep gov x Neg IG growth	0.131	0.356	0.066
	(0.093)	(0.195)	(0.029)
R-squared	0.36	0.37	0.27
R-sq, within	0.04	0.04	0.03
Observations	851	851	1508
States	48	48	48
Years	32	32	32
State FE	By party	By party	By party
Year FE	By party	By party	By party
MOV bandwidth (pp)	16.0	16.0	

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.8.4: Partisan Determinants of Expenditure Growth Components without Partisan Differences: 1983 to 2014

	Household transfers (average: 13% of total)			Interest expenditures (3%)		
	Linear CV	Robust CV	OLS	Linear CV	Robust CV	OLS
Pos IG growth	0.057	-0.397	0.087	0.067	0.349	0.022
	(0.078)	(0.181)	(0.033)	(0.128)	(0.186)	(0.082)
Rep gov x Pos IG growth	-0.063	0.151	0.037	-0.103	-0.159	0.011
	(0.208)	(0.385)	(0.036)	(0.138)	(0.259)	(0.118)
Neg IG growth	0.157	0.205	-0.003	-0.157	-0.453	-0.160
	(0.200)	(0.243)	(0.091)	(0.273)	(0.541)	(0.133)
Rep gov x Neg IG growth	0.300	0.577	0.053	0.173	0.324	0.111
	(0.184)	(0.499)	(0.128)	(0.281)	(0.577)	(0.121)
R-squared	0.66	0.67	0.53	0.31	0.32	0.25
R-sq, within	0.02	0.04	0.01	0.00	0.01	0.00
Observations	576	576	1508	1104	1104	1508
States	47	47	48	48	48	48
Years	32	32	32	32	32	32
State FE	By party	By party	By party	By party	By party	By party
Year FE	By party	By party	By party	By party	By party	By party
MOV bandwidth (pp)	9.0	9.0		24.0	24.0	

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

C.9 Economic Activity

The graph in Figure 7 shows the differential response of state GDP growth to increase and decreases in IG aid growth at different horizons (on impact and up to three years out). The data underlying Figure 7 are taken from Tables C.9.1 and C.9.2. Tables C.9.1 and C.9.2 show that following positive IG growth, states with Democratic governors have relatively higher GDP growth. The robust estimates imply that the GDP level for a Democratic governor is 0.334pp higher for each percent 1pp increase in IG, compared to Republican governor. Qualitatively, higher GDP growth under a Democratic governor lasts up to three years out, even though it is statistically insignificant two years out. For IG cuts, the results are of opposite sign and similar magnitude, but marginally insignificant.

Table C.9.1: Partisan Determinants of Economic Activity Changes: 1983 to 2014 (Impact and 1st Year)

	On impact		1st Year	
	(5) Lin CV	(6) Robust CV	(7) Lin CV	(8) Robust CV
Pos IG growth	0.291	0.217	0.337	0.457
	(0.077)	(0.109)	(0.092)	(0.141)
Rep gov x Pos IG growth	-0.284	-0.334	-0.350	-0.552
	(0.100)	(0.149)	(0.139)	(0.215)
Neg IG growth	-0.195	-0.181	-0.118	-0.417
	(0.123)	(0.164)	(0.083)	(0.272)
Rep gov x Neg IG growth	0.141	0.307	0.125	0.427
	(0.126)	(0.193)	(0.149)	(0.424)
R-squared	0.75	0.77	0.84	0.84
R-sq, within	0.10	0.18	0.23	0.26
Observations	314	314	260	260
States	43	43	41	41
Years	32	32	32	32
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	5.0	5.0	4.0	4.0

Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

Table C.9.2: Partisan Determinants of Economic Activity Changes: 1983 to 2014 (2nd Year and 3rd Year)

	2nd year		3rd year	
	(1) Lin CV	(2) Robust CV	(3) Lin CV	(4) Robust CV
Pos IG growth	0.230	0.290	0.291	0.333
	(0.143)	(0.287)	(0.138)	(0.185)
Rep gov x Pos IG growth	-0.135	-0.378	-0.213	-0.492
	(0.169)	(0.318)	(0.195)	(0.238)
Neg IG growth	-0.053	-0.053	-0.247	0.718
	(0.164)	(0.240)	(0.475)	(0.965)
Rep gov x Neg IG growth	-0.094	0.237	0.002	-0.670
	(0.201)	(0.292)	(0.493)	(0.960)
R-squared	0.86	0.87	0.89	0.89
R-sq, within	0.09	0.12	0.11	0.16
Observations	303	303	287	287
States	43	43	42	42
Years	31	31	30	30
State FE	By party	By party	By party	By party
Year FE	By party	By party	By party	By party
MOV bandwidth (pp)	5.0	5.0	5.0	5.0

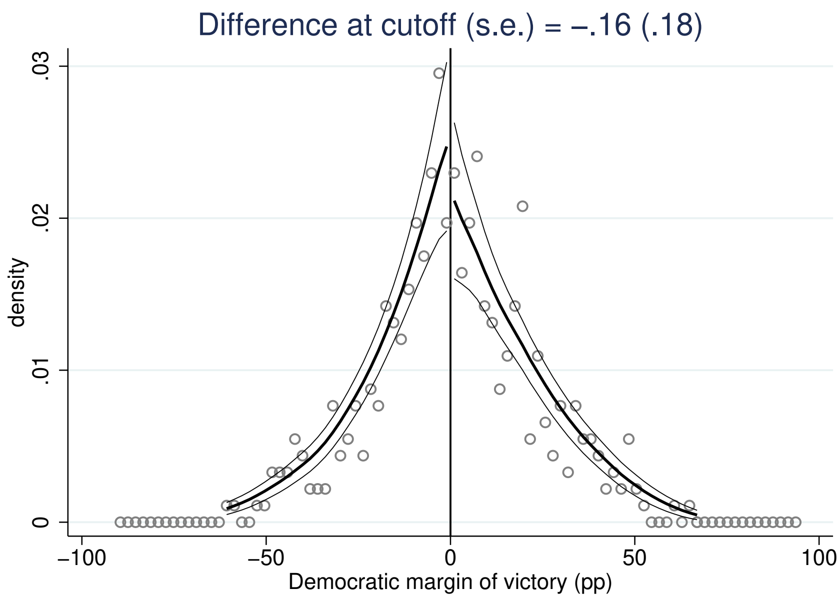
Notes: Estimated MOV polynomials not shown. Standard errors clustered by state and year.

D Additional Figures

D.1 McCrary test

An issue with regression discontinuity designs is whether the units can manipulate their score on the running variable. McCrary (2008) proposes a test of manipulation related to continuity of the running variable density function. Figure D.1.1 applies the McCrary test for manipulation of the Democratic MOV (collapsed to the state-election level). The test fails to reject the Null of a discontinuity of the running variable.

Figure D.1.1: McCrary (2008) Test: 1983-2014



Note: The Observations Have Been Collapsed to the State-Election Level.

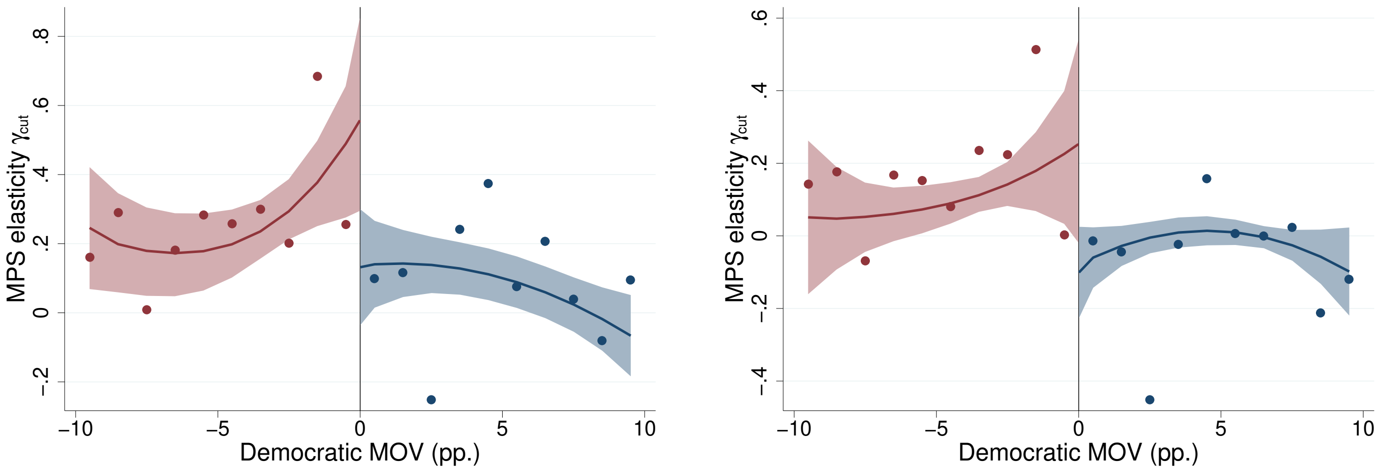
D.2 Negative IG shocks

Figure D.2.1 is like Figure 2 in the paper, except that Figure D.2.1 shows the governors' response to cuts in IG aid. Figure D.2.1 shows that Republican governors pass more of IG aid decreases on to spending cuts. That is, governors' responses to cuts in IG aid also show significant partisan differences as the MOV approaches zero, but of opposite sign.

Figure D.2.1: Illustrating Our Regression Discontinuity in Slopes, 1983–2014: Republican Governors Pass More of IG Decreases on to Spending Cuts.

Without fixed effects
(a) Without fixed effects

With party × (year, state) fixed effects
(b) With party × (year, state) fixed effects



The plots show the estimated marginal propensity to spend (MPS) elasticity along with $\pm 1(\pm 1.65)$s.e. clustered by year and state for each 1pp MOV bin. The standard errors are computed point wise by estimating (2.2) without MOV controls with party×year and party×state fixed effects (or without any fixed effects) and all slope coefficients and intercepts interacted with dummies for each MOV bin. Overlaid are linear regressions weighted by the inverse squared s.e.

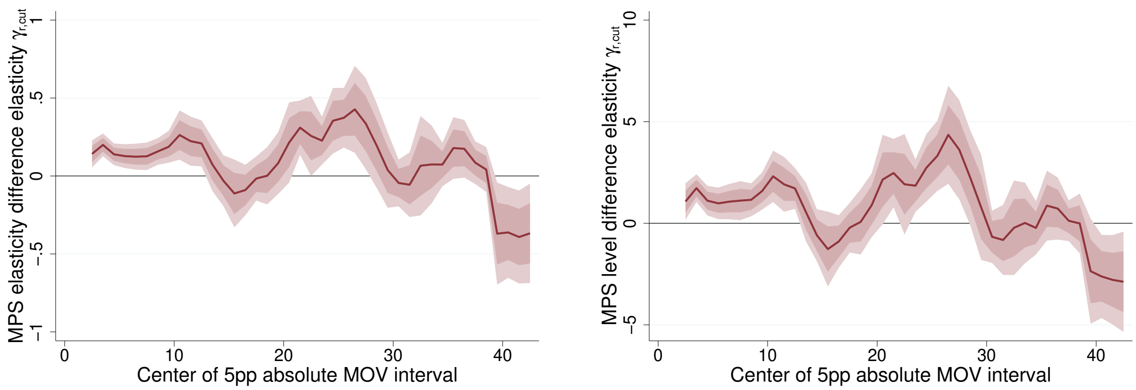
D.3 OLS estimates for various MOVs

"Are partisan differences only evident in close windows?" To tackle this question, we estimate partisan differences in pass-throughs in varying 5pp. buckets (i.e. elections with a 5% to 10% absolute margin of victory). Figure 4 shows the results for IG increases; we now show the results for IG cuts in Figure D.3.1. In the left panel of Figure D.3.1, partisan differences are evident for absolute margin of victories within 35%, which makes up over 80% of our observations. We do not find evidence of partisan difference in the tail of margin of victories.

Figure D.3.1: MPS Elasticity Estimates for IG Cuts by 5pp Absolute MOV Ranges

(a) Elasticity estimate

(b) Level estimate



E Model appendix

E.1 Households

The economy consists of two representative regions, with (population) measures of $n \in (0,1)$ and $1-n$, respectively. Two types of households live within each region. A measure $\mu \in (0,1]$ of households is unconstrained, while a measure $1-\mu$ of households has no access to saving or borrowing. Each household has the same labor endowment and supplies labor elastically.

Constrained home households Constrained households consume their entire income. They maximize utility by setting their labor supply N_t^c and consuming the proceeds.

$$U_t^c = \max_{\{C_s^c, N_s^c\}_{s\geq t}} \mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} \tilde{u}(C_s^c, N_s; G_s^{st}) \tag{E.1}$$

$$P_t C_t^c \leq W_t N_t^c + Tr_t + Pr_t^c \tag{E.2}$$

Optimality:

$$\tilde{u}_{c,t}((1-\tau_t)w_t N_t^c + tr_t + pr_t^c, N_t^c; G_s^{st})(1-\tau_t)\frac{W_t}{P_t} = -\tilde{u}_{N,t}((1-\tau_t)w_t N_t^c + tr_t + pr_t^c, N_t^c; G_s^{st}). \tag{E.3}$$

Preferences:

$$\tilde{u}(C, N; G^{st}) = \frac{C^{1-1/\epsilon_c} - 1}{1-1/\epsilon_c} - \kappa_N^c \frac{N^{1+1/\epsilon_N}}{1+1/\epsilon_N} + v(G^{st}).$$

with

$$\tilde{u}_c = C^{-1/\epsilon_c}$$
$$\tilde{u}_N = -\kappa_N^c N^{1/\epsilon_N}$$

Or

$$\tilde{u}(C, N; G^{st}) = \frac{\left(C - \kappa_N^c \frac{N^{1+1/\epsilon_N}}{1+1/\epsilon_N}\right)^{1-1/\epsilon_c} - 1}{1-1/\epsilon_c} + v(G^{st}).$$

with

$$\tilde{u}_c = \left(C - \kappa_N^c \frac{N^{1+1/\epsilon_N}}{1+1/\epsilon_N}\right)^{-1/\epsilon_c}$$
$$\tilde{u}_N = -\left(C - \kappa_N^c \frac{N^{1+1/\epsilon_N}}{1+1/\epsilon_N}\right)^{-1/\epsilon_c} \kappa_N^c N^{1/\epsilon_N} = -\tilde{u}_c \kappa_N^c N^{1/\epsilon_N}$$

For future reference, let lowercase letters denote the real counterpart of nominal variables, e.g., $w_t \equiv \frac{W_t}{P_t}$.

1. Separable preferences:

$$(1-\tau_t)w_t = \kappa_N^c (N_t^c)^{1/\varepsilon_N}((1-\tau_t)w_t N_t^c + tr_t + pr_t^c)^{1/\epsilon_C}. \tag{E.4}$$

   Given w_t, this equation implicitly pins down labor supply.

   With zero transfers and profits:

$$((1-\tau_t)w_t)^{1-\frac{1}{\varepsilon_C}} = \kappa_N^c (N_t^c)^{1/\varepsilon_C + 1/\varepsilon_N} \quad \Leftrightarrow \quad N_t^c = \left(\frac{((1-\tau_t)w_t)^{1-\frac{1}{\varepsilon_C}}}{\kappa_N^c}\right)^{\frac{1}{1/\varepsilon_C + 1/\varepsilon_N}} \quad \forall t.$$

   With log utility, income and substitution effects cancel each other out.

2. GHH preferences:

$$(1-\tau_t)w_t = \kappa_N^c (N_t^c)^{1/\varepsilon_N}. \tag{E.5}$$

   There is no wealth effect on labor supply.

   Linearized:

$$\hat{w}_t - \frac{\bar{\tau}^{st}\hat{\tau}_t^{st} + \bar{\tau}^f \hat{\tau}_t^f}{1-\bar{\tau}} = \frac{1}{\varepsilon_N}\hat{N}_t^c \tag{E.6}$$

   But marginal utility of consumption increases when N increases, giving rise to a complementarity between consumption and hours worked.

$$\hat{u}_c = \frac{-\frac{\bar{C}}{\varepsilon_C}\hat{C} + \frac{1}{\varepsilon_N \varepsilon_C}\kappa_N^C \bar{N}^{1/\varepsilon_N}\hat{N}}{\bar{C} - \kappa_N^c \frac{\bar{N}^{1+1/\varepsilon_N}}{1+1/\varepsilon_N}} \tag{E.7}$$

Unconstrained home households Unconstrained households choose consumption C_t^u, real bond holdings B_{t-1}^u/P_t, labor supply N_t^u, investment I_t^u, capacity utilization u_t, and physical capital K_{t-1} to maximize lifetime utility subject to the budget constraint, and the law of motion for capital.

$$U_t^u = \max_{\{C_s^u, B_s^u, N_s^u, I_s, u_s, K_s\}_{s\geq t}} \mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} u(C_s^u, B_{s-1}^u/P_t, N_s; G_s^{st}) \tag{E.8}$$

$$P_t C_t^u + B_t^u \leq (1-\tau_t)W_t N_t^u + B_{t-1}^u R_{t-1}^n + Tr_t + Pr_t \tag{E.9}$$

In the presence of complete markets, the household can also purchase a set of Arrow-Debreu securities at the beginning of time.

We model preferences of the unconstrained households as having the same functional form as those by the constrained households plus an additively separable demand for bond holdings:

$$u(C, b, N; G^{st}) = \tilde{u}(C, N; G^{s}t) + \kappa_b \frac{b^{1-1/\epsilon_b}}{1 - 1/\epsilon_b}. \tag{E.10}$$

This implies that the ratio of substitution between consumption and bonds is given by:

$$\frac{u_b}{u_c} = \kappa_b b^{-1/\epsilon_b} C^{1/\epsilon_c}. \tag{E.11}$$

Using $\beta^t \lambda_t$ as the Lagrange multipliers on (E.9), the FOC are given by:

$$\begin{aligned}
&[C] \qquad & u_{c,t} &= \lambda_t P_t \\
&[N] \qquad & u_{N,t} &= -\lambda(1 - \tau_t) W_t \\
&[B] \qquad & \lambda_t &= \mathbb{E}_t \left[\beta \left(\frac{u_{b,t+1}}{P_{t+1}} + \lambda_{t+1} R_t^n \right) \right]
\end{aligned}$$

Eliminating λ_t and defining $M_{t+1}^n \equiv \beta \frac{u_{c,t+1}}{u_{c,t}} \frac{P_t}{P_{t+1}}$:

$$[N] \qquad \frac{-u_{N,t}}{u_{c,t}} = (1 - \tau_t) \frac{W_t}{P_t} \tag{E.12}$$

$$[B] \qquad 1 = \mathbb{E}_t \left[M_{t+1}^n \left(\frac{u_{b,t+1}}{u_{c,t+1}} + R_t^n \right) \right] \tag{E.13}$$

Private sector demand. Total home consumption is given by:

$$C_t = \mu C_t^u + (1 - \mu) C_t^c. \tag{E.14}$$

$$N_t = \mu N_t^u + (1 - \mu) N_t^c. \tag{E.15}$$

Total home bond holdings are given by:

$$B_t = \mu B_t^u. \tag{E.16}$$

Following Nakamura and Steinsson (2014), the composite consumption (and investment) good is given by an aggregate of home and foreign varieties:

$$C_t = \left(\phi_H^{1/\eta} C_{Ht}^{1-1/\eta} + \phi_F^{1/\eta} \right)^{\frac{\eta}{\eta-1}}, \quad \phi_F = 1 - \phi_H, \tag{E.17}$$

where the individual varieties enter as follows:

$$C_{Xt} = \left(\int_0^1 c_{xt}(z)^{1-1/\theta} dz \right)^{\frac{\theta}{\theta-1}}, \qquad X \in \{H, F\}. \tag{E.18}$$

All individual prices p_{xt} are denominated in “dollars” and common across regions.

The corresponding price indices and individual demands are:

$$C_{Xt} = \phi_X C_t \left(\frac{P_{Xt}}{P_t}\right)^{-\eta} \tag{E.19}$$

$$c_{xt}(z) = C_{Xt} \left(\frac{p_{xt}(z)}{P_{Xt}}\right)^{-\theta} \tag{E.20}$$

$$P_{Xt} = \left(\int_0^1 p_{xt}(z)^{1-\theta} dz\right)^{\frac{1}{1-\theta}} \tag{E.21}$$

$$P_t = \left(\phi_H P_{Ht}^{1-\eta} + \phi_F P_{Ft}^{1-\eta}\right)^{\frac{1}{1-\eta}}. \tag{E.22}$$

Foreign households. The foreign region is set up symmetrically, with equal demand elasticities and an analogous home bias $\phi_H^* > 1 - n$. $*$ superscripts denote foreign demands.

Perfect risk sharing. With perfect risk sharing we have that:

$$X_t \equiv \frac{P_t^*}{P_t} = M_t \equiv M_t^n \frac{P_{t+1}}{P_t}. \tag{E.23}$$

Also assume that, initially, $NFA_t = 0$.

E.2 Firms

Within each region, there is a unit measure of firms, indexed by z. Firms produce

$$y_{xt}(z) = A_t N_t(z)^{1-\alpha}. \tag{E.24}$$

Firms face a demand curve given by:

$$D_{ht} = D_{Ht} \left(\frac{p_{ht}(z)}{p_{Ht}}\right)^{-\theta}.$$

Optimal factor demands satisfy:

$$[N_t(z)] \qquad W_t = (1-\alpha)\frac{y_{xt}(z)}{N_t(z)} MC_{ht}(z). \tag{E.25}$$

Firms can only reset prices with probability $1 - \xi$ and otherwise increase prices at an exogenous rate $\bar{\Pi} \geq 1$. Home firms' objective is therefore:

$$\mathbb{E}_t \sum_{s=0}^{\infty} \left(\prod_{u=0}^{s-1} M_{t+u}^n \xi\right) \left(P_{h,t}(z)\bar{\Pi}^s D_{H,t+s} \left(\frac{\bar{\Pi}^s P_{h,t}(z)}{P_{H,t+s}}\right)^{-\theta} - W_{t+s} N_{t+s}(z)\right) \tag{E.26}$$

$$= \mathbb{E}_t \sum_{s=0}^{\infty} \left(\prod_{u=0}^{s-1} M_{t+u}^n \xi\right) \left(P_{h,t}(z)\bar{\Pi}^s D_{H,t+s} \left(\frac{\bar{\Pi}^s P_{h,t}(z)}{P_{H,t+s}}\right)^{-\theta} - (1-\alpha) MC_{ht} D_{H,t+s} \left(\frac{\bar{\Pi}^s P_{h,t}(z)}{P_{H,t+s}}\right)^{-\theta}\right). \tag{E.27}$$

Optimal pricing:

$$P_{ht}(z) = \frac{\theta}{\theta-1}\frac{CN_t^n}{CD_t}, \tag{E.28}$$

where

$$CN_t^n \equiv \mathbb{E}_t \sum_{j=0}^{\infty} (\bar{\Pi}^{-\theta}\xi)^j \left(\prod_{u=0}^{j-1} M_{t,t+u}^n\right) y_{h,t+j}(z) MC_{t+j}(z), = y_{h,t}(z) MC_t^n(z) + \mathbb{E}_t[M_{t,t+1}^n \bar{\Pi}^{-\theta}\xi CN_{t+1}^n].$$

$$CD_t \equiv \mathbb{E}_t \sum_{j=0}^{\infty} (\bar{\Pi}^{1-\theta}\xi)^j \left(\prod_{u=0}^{j-1} M_{t,t+u}^n\right) y_{h,t+j}(z) = y_{h,t}(z) + \mathbb{E}_t[M_{t,t+1}^n \bar{\Pi}^{1-\theta}\xi CD_{t+1}].$$

For foreign producers, the above expression applies with discount factor $M_{t,t+1}^{n*}$ and with (f, F) replacing (h, H).

Equivalently, the real target price is:

$$p_{ht}(z) \equiv \frac{P_{ht}(z)}{P_t} = \frac{\theta}{\theta-1}\frac{CN_t}{CD_t}, \tag{E.29}$$

where

$$CN_t = y_{h,t}(z) MC_t^r(z) + \mathbb{E}_t[M_{t,t+1}^n \Pi_{t+1}\bar{\Pi}^{-\theta}\xi CN_{t+1}].$$

In the foreign region, the real target price is:

$$p_{ft}(z) \equiv \frac{P_{ft}(z)}{P_t} = \frac{\theta}{\theta-1}\frac{CN_t^*}{CD_t^*}, \tag{E.30}$$

where

$$CN_t^* = y_{f,t}(z)\frac{MC_t^{n^*}(z)}{P_t^*} X_t + \mathbb{E}_t[M_{t,t+1}^{n^*} \Pi_{t+1}\bar{\Pi}^{-\theta}\xi CN_{t+1}^*].$$

Note that CN_t^* is expressed relative to home currency prices, and the future inflation rate is also that of the home region.

The home producer price index becomes:

$$\begin{aligned} P_{Ht} &= \left((1-\xi)P_{ht}(z)^{1-\theta} + \xi(P_{H,t-1}\bar{\Pi})^{1-\theta}\right)^{\frac{1}{1-\theta}} \\ \Leftrightarrow \quad \Pi_{H,t} \equiv \frac{P_{Ht}}{P_{H,t-1}} &= \left((1-\xi)\left(\frac{P_{ht}(z)}{P_t}\frac{P_t}{P_{H,t}}\Pi_{H,t}\right)^{1-\theta} + \xi\bar{\Pi}^{1-\theta}\right)^{\frac{1}{1-\theta}} \\ \Leftrightarrow \quad \Pi_{Ht}^{1-\theta} &= (1-\xi)\left(\frac{p_{ht}}{p_{Ht}}\Pi_{H,t}\right)^{1-\theta} + \xi\bar{\Pi}^{1-\theta} \end{aligned}$$

Similarly, foreign producer price inflation is given by:

$$\Pi_{Ft}^{1-\theta} = (1-\xi)\left(\frac{p_{ft}}{p_{Ft}}\Pi_{F,t}\right)^{1-\theta} + \xi\bar{\Pi}^{1-\theta}.$$

using that p_{Ft} is also expressed relative to P_t.

Note that by definition:

$$\Pi_{Ht} \equiv \frac{P_{Ht}}{P_{H,t-1}} = \frac{p_{Ht}}{p_{H,t-1}}\Pi_t \quad \Leftrightarrow \quad p_{Ht} = \frac{\Pi_{Ht}}{\Pi_t}p_{H,t-1}. \tag{E.31}$$

E.3 Government

We are considering the cash-less limit, in which monetary policy does not generate revenue for the government.

Monetary authority The monetary authority sets interest rates according to:

$$R_t^n = (\bar{\Pi}/\beta)^{\rho_r}\left(\left(\frac{\bar{\Pi}_t}{\bar{\Pi}}\right)^{\psi_{r\pi}}\left(\frac{\bar{Y}_t}{\bar{Y}}\right)^{\psi_{ry}}\right)^{1-\rho_r}, \tag{E.32}$$

$$\bar{\Pi}_t \equiv n\Pi_t + (1-n)\Pi_t^*, \tag{E.33}$$

$$\bar{Y}_t \equiv nY_t + (1-n)Y_t^*. \tag{E.34}$$

State governments

$$G_{st,t} = \psi_{IG}\left(\frac{IG_t}{P_t} - \bar{I}G\right) + G_{st,t}^x$$

$$G_{st,t}^x = (1-\rho_{st,g})\bar{G}^{st} + \rho_{st,g}G_{st,t-1}^x + \omega_{st,g}\epsilon_{st,t}^x$$

States adjust labor taxes to finance the current deficit:

$$(1-\gamma^s)((R_{t-1}^n - 1)B_{t-1}^{st} - (\bar{R}^n - 1)\frac{\bar{b}^{st}}{\bar{\Pi}}P_t) + P_tG_t^{st} - P_t\bar{G}_t^{st} - (IG_t - P_t\bar{I}G)+) = \tau_t^{st}W_tN_t - \bar{\tau}^{st}P_t\bar{w}\bar{N}. \tag{E.35}$$

The remainder of the budget is financed through debt issuance. The budget is:

$$P_tG_t^{st} + Tr_t^{st} + R_{t-1}^nB_{t-1}^{st} = B_t^{st} + IG_t + \tau_t^{st}W_tN_t. \tag{E.36}$$

Federal government. The federal government levies lump-sum and distortionary taxes to finance federal government consumption and to provide intergovernmental transfers to states. Nominal per capita transfers are equal to IG_t in each region.

For simplicity, federal transfers and real per capita purchases in the states are exogenous:

$$IG_t = \rho_{IG} IG_{t-1} + \omega_{IG}\epsilon_{IG,t}. \tag{E.37}$$

$$G_t^f = \rho_{Gf} G_{t-1}^f + \omega_{Gf}\epsilon_{Gf,t}. \tag{E.38}$$

Purchases equal real per capita amounts $G_{Ht}^f = G_{Ft}^f = G_t^f$ per region (exogenous).

Nominal budget

$$(nP_t + (1-n)P_t^*)G_t^f + IG_t + Tr_t^f + R_{t-1}^n B_{t-1}^f = \tau_t^f (nW_t N_t + (1-n)W_t^* N_t^*) + B_t^f \tag{E.39}$$

Similar to state governments, labor income taxes finance a fraction of the budget every period (out of steady state):

$$\begin{aligned}(1-\gamma^f)((R_{t-1}^n - 1)B_{t-1}^f - (\bar{R}^n - 1)P_t \frac{\bar{b}^f}{\bar{\Pi}} + (nP_t + (1-n)P_t^*)G_t^f - \bar{P}\bar{G}^f + IG_t - \overline{IG}) \\ = \tau_t^f (nW_t N_t + (1-n)W_t^* N_t^*) - \bar{\tau}^f \bar{W}\bar{N}.\end{aligned} \tag{E.40}$$

The federal government finances the remaining fraction γ^f of expenditures via nominal debt issuance.

E.4 Market clearing

Market clearing implies:

$$b_t^f = n(b_t - b_t^{st}) + (1-n)(b_t^* - b_t^{st*}) \tag{E.41}$$

$$N_t = \mu N_t^u + (1-\mu)N_t^c \tag{E.42}$$

$$N_t^* = \mu N_t^{u*} + (1-\mu)N_t^{c*} \tag{E.43}$$

$$Y_t = Y_{Ht} = nD_t \left(\frac{P_{Ht}}{P_t}\right)^{-\eta} + (1-n)D_t^* \left(\frac{P_{Ht}}{P_t^*}\right)^{-\eta} \tag{E.44}$$

$$Y_t^* = Y_{Ft} = nD_t \left(\frac{P_{Ft}}{P_t}\right)^{-\eta} + (1-n)D_t^* \left(\frac{P_{Ft}}{P_t^*}\right)^{-\eta} \tag{E.45}$$

where $D_t = \phi_H C_t + \phi_H G_t^{st} + G_t^f$.

Normalization:

$$P_t = 1 \tag{E.46}$$

E.5 Steady state

The model is calibrated at a quarterly frequency.

Labor supply. We choose κ_N^c, κ_N^u such that $\bar{N}^c = \bar{N}^u = 1$.

Aggregate output. We normalize output in both states (regions) to 1, so that $\bar{A} = \bar{N}^{-(1-\alpha)}$.

Overall consumption. Calibrating the combined government spending to GDP ratio yields the aggregate consumption to GDP ratio, given the capital to output ratio:

$$\frac{\bar{C}}{\bar{Y}} = 1 - \frac{\bar{G}}{\bar{Y}}. \quad \Rightarrow \quad \bar{C} = 1 - \frac{\bar{G}}{\bar{Y}}$$

under the normalization that $\bar{Y} = 1$.

Group consumption. Constrained agents' consumption follows from their budget constraint, given the calibration assumption that they provide the same amount of labor in steady state:

$$\frac{\bar{C}^c}{\bar{Y}} = (1-\alpha)\left(1 - \frac{1}{\theta}\right)(1 - \bar{\tau}^f - \bar{\tau}^{st}) + \frac{tr^{st} + \mathrm{tr}^f}{\bar{Y}} + \kappa^c_{pr}\frac{1}{\theta}.$$

Consumption of the unconstrained is the residual:

$$\frac{\bar{C}^u}{\bar{Y}} = \frac{1}{\mu}\frac{\bar{C}}{\bar{Y}} - \frac{1-\mu}{\mu}\frac{\bar{C}^c}{\bar{Y}}$$

Monetary policy. Absent a premium for government securities, the nominal interest rate is simply:

$$\bar{R}^n = \frac{1}{\beta}\frac{1}{\bar{\Pi}}.$$

Federal government.

$$\frac{\overline{tr}^f}{\bar{Y}} = \bar{\tau}^f(1-\alpha)\left(1 - \frac{1}{\theta}\right) - \frac{\bar{G}^f}{\bar{Y}} - \frac{\bar{I}G}{\bar{Y}} - \left(\frac{\bar{R}^n}{\bar{\Pi}} - 1\right)\frac{\bar{b}^f}{\bar{Y}},$$

where $\frac{\bar{b}}{\bar{Y}} = 0.7 \times 4$ and $\frac{\bar{I}G}{\bar{Y}} = 0.05$ and $\bar{\tau}^f = 0.30$.

We also calibrate $\frac{\bar{G}}{\bar{Y}} = 0.20$ and $\frac{\bar{G}^f}{\bar{Y}} = 0.6\frac{\bar{G}}{\bar{Y}} = 0.12$.

State government.

$$\frac{\overline{tr}^{st}}{\bar{Y}} = \bar{\tau}^{st}(1-\alpha)\left(1 - \frac{1}{\theta}\right) - \frac{\bar{G}^{st}}{\bar{Y}} + \frac{\bar{I}G}{\bar{Y}} - \left(\frac{\bar{R}^n}{\bar{\Pi}} - 1\right)\frac{\bar{b}^{st}}{\bar{Y}},$$

where $\frac{\bar{b}}{\bar{Y}} = 0.05 \times 4$ and $\frac{\bar{I}G}{\bar{Y}} = 0.05$ and $\bar{\tau}^{st} = 0.05$.

Constrained households We choose κ_N^c such that $\bar{N}^c = \bar{N}^u = \bar{N} = 1$.

$$\kappa_N^c = (1-\tau)(1-\alpha)(1-\frac{1}{\theta})(\bar{N}^c)^{-(1+1/\varepsilon_N)}\bar{Y}(C^c)^{-1/\epsilon_C}. \tag{E.47}$$

under separable preferences and

$$\kappa_N^c = (1-\tau)(1-\alpha)(1-\frac{1}{\theta})(\bar{N}^c)^{-(1+1/\varepsilon_N)}\bar{Y}. \tag{E.48}$$

under GHH preferences.

Consumption follows from the budget constraint as:

$$\frac{(1-\mu)\bar{C}^c}{\bar{Y}} = (1-\bar{\tau})(1-\alpha)(1-\frac{1}{\theta})(1-\mu) + (1-\mu)\frac{Tr}{\bar{Y}} + (1-\mu)\kappa_{Pr}^c\frac{1}{\theta}, \tag{E.49}$$

where κ_{Pr}^c determines which fraction (if any) of profits households receive.

Unconstrained households κ_N^u is determined analogously as for the constrained households.

E.6 Fiscal rule estimates

Table E.6.1: Full Sample Estimate of the Tax Adjustment Rule

	(1)	(2)	(3)	(4)
Lagged tax rate		-0.1191***	-0.1192***	-0.1901***
		(-6.40)	(-6.43)	(-7.24)
Lagged interest on debt (% change)	0.0005**	0.0005**	0.0005**	0.0006*
	(2.29)	(2.04)	(2.04)	(1.99)
Exp Growth	0.0064***	0.0056***		
	(5.19)	(4.74)		
IG transfers (% change)	-0.0011*	-0.0010*		
	(-1.87)	(-1.83)		
Exp net of IG (% change)			0.0055***	0.0046***
			(4.70)	(4.07)
R-squared	0.34	0.38	0.38	0.44
R-sq, within	0.02	0.08	0.08	0.12
Observations	2372	2372	2372	1499
States	50	50	50	48
Years	50	50	50	32
StateFE	Yes	Yes	Yes	Yes
YearFE	By region	By region	By region	By region
IG to Exp	0.25	0.25	0.25	0.25
Net expenditure to GDP			0.09	0.09
Coefficient G net of IG			0.070	0.064
Debt to GDP			0.07	0.07
Interest on debt to GDP		0.004	0.004	0.004
Coefficient Int on Debt		0.158	0.158	0.217
Annual persistence		0.88	0.88	0.81

E.7 Separable Results

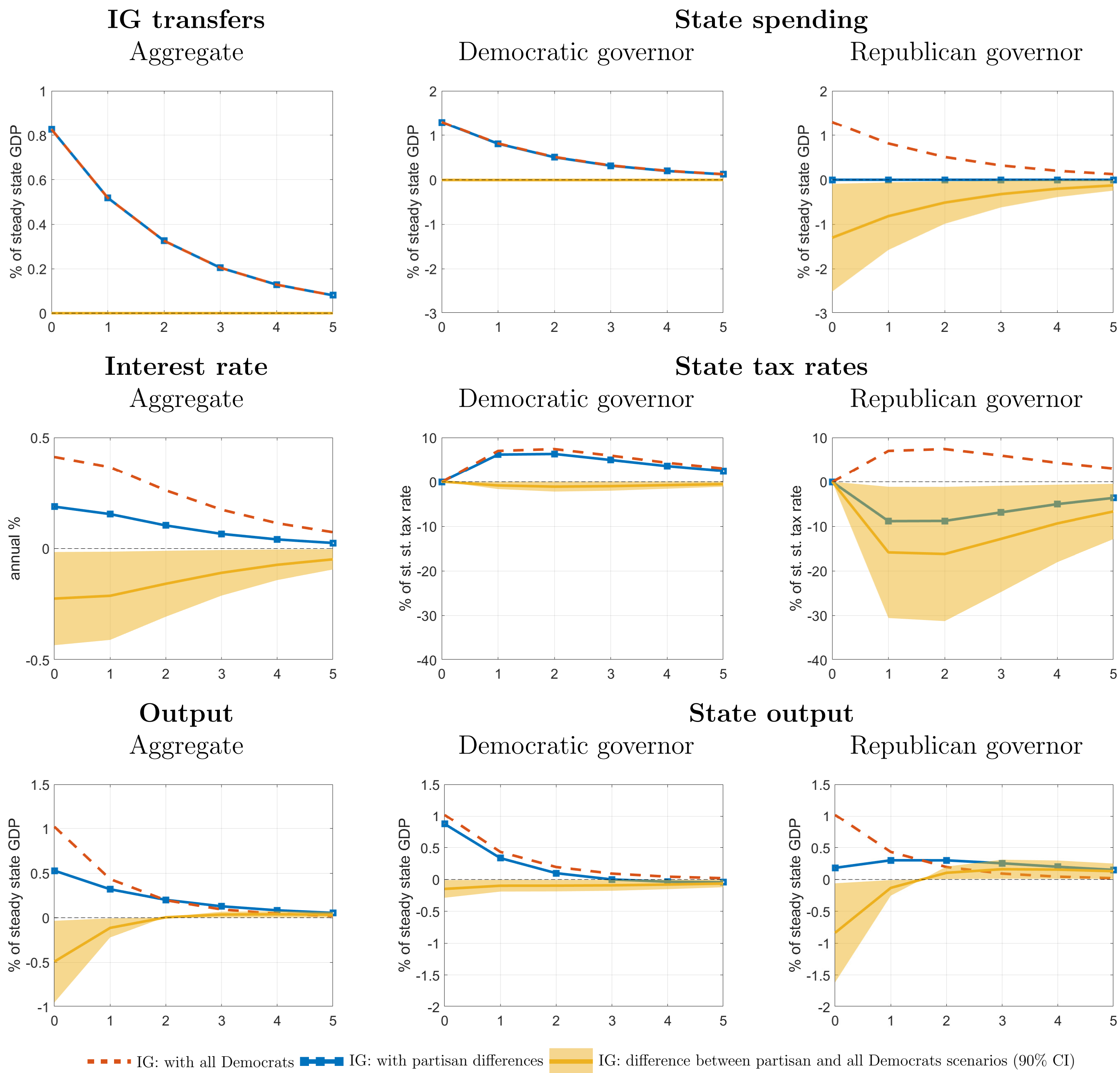
The Republican governor has the same MPS as the Democratic governor. The difference between these two scenarios is the effect of the partisan MPS differences. The thin solid line with the surrounding band shows the point estimate of these differences with its 90% confidence interval. The panels in the first row of Figure E.7.1 show the path of the IG transfer shock and the state spending responses in the Democratic and Republican states. The top left panel shows the increased federal transfers. Transfers initially increase by 0.82% of GDP and have a half-life of 1.5 years. Since transfers are exogenous, they are the same in both scenarios of partisanship. The top middle panel shows the spending response in the Democratic state. It always has an MPS of 1.576; spending increases by 1.29% of GDP (=1.576×0.82%) on impact. It then declines as the shock to IG aid gradually declines over time; the solid and dashed lines overlap in this case. The top right panel shows the spending response in the Republican state with either the baseline MPS of zero (solid line with squares) or with the counterfactual Democratic MPS of 1.576 (dashed line). Since spending depends only on IG transfers and the MPS, it is zero in the baseline scenario for the Republican state, and equal to that in the Democratic state without partisan differences. The narrow line with its 90% confidence band shows the estimated (negative) partisan effect on spending in the Republican state (first row, right panel). With the Republican MPS, state spending is statistically significantly lower (below zero) than with a Democratic MPS. Given an increase in IG aid, Democrats increase spending.

The center rows of Figure E.7.1 show the path of interest rates and state taxes. In response to the increased state spending, inflation and the aggregate output gap rise, prompting an interest rate increase of about 0.2 percent with partisan politics. In the counterfactual with only Democratic governors, the increase would be twice as high, at 0.4 percent, reflecting the increased spending. The middle panel shows Democratic tax rates, as a percent of their steady state value. With an MPS greater than unity, Democratic states must increase state labor income taxes to pay for increased spending above the $1 of new IG aid. As a result, state labor income tax rates must rise, rising by up to 6.3% of the steady state rate (or 0.32pp) after one year and slowly declining towards zero starting in the third year. The tax increase is only slightly higher in response to Republican state changes (dashed line). In the Republican state, spending does not increase. Increases in IG aid are allocated to tax cuts and state tax rates fall, shown as the declining line with squares (center row, right panel). When the Republican state is assigned the MPS of Democratic states, however, state labor income taxes now rise, along the "Democratic" dashed line. Again the estimated partisan difference in tax responses is shown by the narrow line with its 90% confidence band in the center row, right panel. The estimated level of Republican state taxation is shown as significantly lower than that under Democratic state policies and centered at -16.0% of steady state taxes (0.8 pp), after two years. The shaded 90% confidence interval for this difference is (-1.1% to -30.9%). Given an increase in IG aid, Republican states cut taxes.

The difference in fiscal policies across Republican and Democratic states leads to significant differences in the paths of state output and in aggregate national output. The bottom middle panel of Figure E.7.1 shows the path of Democratic state output rises by 1.0% on impact and by .45% after one year when only Democratic states raise state spending (solid line with squares). Republican states, which do not raise state spending but instead cut taxes, have initially more modest gains in state output, shown as the solid line with squares in the bottom right panel: If, however, Republican states were to spend IG transfers as do Democratic states (dashed line) they would also enjoy significant gains in state output. The end result is significantly lower output gains in Republican states because of their decision to allocate IG transfers to tax cuts rather than spending. On impact, output increases by .84% of GDP less than with a Democratic MPS, with a 90% confidence interval of (-.06%, -1.62%). Starting in year three, however, output is relatively higher (by 0.11%) due the Republican policies. This benefit of the Republican tax cuts persists. The partisan difference in policy leads to small fiscal spillovers, lowering the output in the Democratic state slightly – by 0.1% on impact.

Finally, the nation as a whole and also Democratic states enjoy less output gains in the short-run because Republican states do not spend IG transfers. The higher dashed line in the bottom left panel of Figure E.7.1 shows national output gains if all states spent IG transfers as do Democratic states. It implies an output gain of 1.0% on impact – which would be equally shared by the two states, as shown by the dashed lines in all bottom panels. National output gains with partisan differences are about half as high: Output grows by only 0.5% (line with squares; bottom left) on impact. For the first two years, output is lower with the partisan differences in spending due to the fact that spending aggregated across the two (equal-sized) states is only half as high with partisan policies. However, higher taxes in Democratic states and lower taxes in Republican states mean that, starting in year three, aggregate output is slightly larger (about 0.05%) with partisan differences. While small, these differences accumulate and lead to a trade-off between the impact multiplier and the long-run multiplier.

Figure E.7.1: Impulse Responses: Spending, Taxes and Output, Separable Preferences

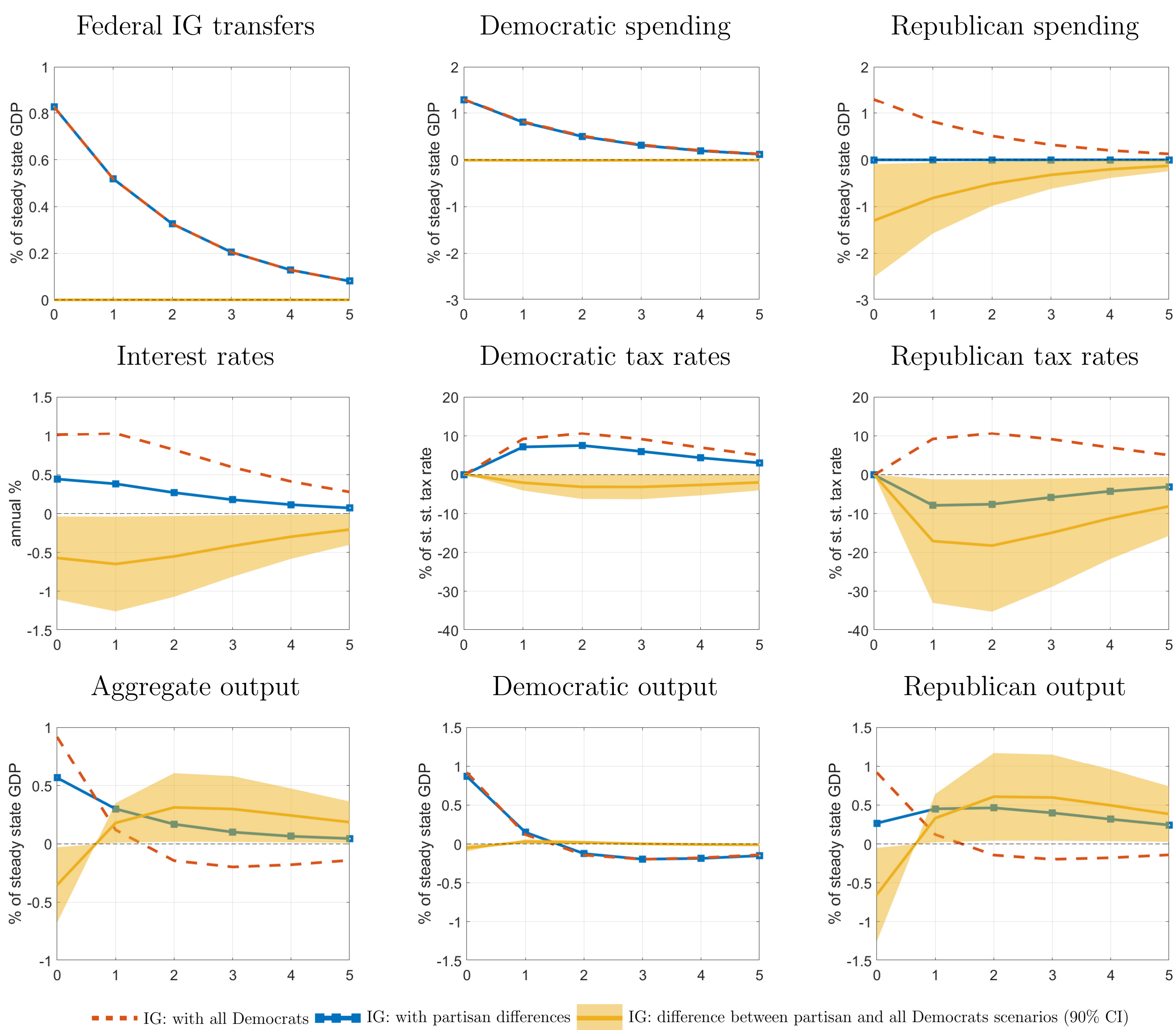


Impulse responses (relative to steady state) to IG transfer shock shown for two scenarios: (1) with partisan differences (solid line with squares) with one state run by a Democratic governor (middle column) and the other by a Republican governor (right column), and (2) when both states have the preferences of Democratic governors (dashed line). The thin solid with its 90th percentile confidence interval as the shaded area shows the difference in responses between the two scenarios. For example, the top right panel implies that a Republican governor does not increase spending (blue line with markers), whereas spending would rise initially by 1.29% of GDP if the state had a Democratic governor. The 90% confidence interval for the difference between these two scenarios is $(-0.09, -2.49)$.

E.8 Results with GHH preferences

In Figure E.8.1, we provide corresponding impulse response functions for GHH preferences. The top panel, which shows the fiscal spending impulses, is identical to the previous case with separable household preferences, because it reflects only governors' preferences. There are small differences in the center panel, for interest rates and state tax rates, because these are driven by policy rules and partly endogenous. The main differences concern the bottom row, which shows aggregate and state output. Without partisan preferences, the output increase is less persistent, because the tax increases now exert a stronger drag on the economy, as the negative substitution effect is not partly offset by income effects as is the case with the separable household preference specification. For the same reason, output in the Republican-led state rises somewhat more with partisan preferences in this case of GHH preferences. Together, these effects imply a reversal of the relative output effects. With GHH preferences, output in both states and in aggregate is noticeably higher when Republican-led states enact tax cuts.

Figure E.8.1: Impulse Responses: Spending, Taxes and Output, GHH Preferences



Impulse responses (relative to steady state) to IG transfer shock shown for two scenarios: (1) with partisan differences (solid line with squares) with one state run by a Democratic governor (middle column) and the other by a Republican governor (right column), and (2) when both states have the preferences of Democratic governors (dashed line). The thin solid with its 90th percentile confidence interval as the shaded area shows the difference in responses between the two scenarios.

E.9 Summary of calibrated parameters

Table E.9.1: Calibrated Parameters

	Parameter	Value	Source
households	Intertemporal elasticity of substitution ϵ_c	1	Nakamura and Steinsson (2014)
	Frisch elasticity of labor supply ϵ_N	3	Prescott (2004)
	Annual real interest rate	2%	Data
	Share of credit constrained households μ	0.35	Coenen et al. (2012)
	Price elasticity of demand across states η	2	Nakamura and Steinsson (2014)
	Price elasticity of demand within states θ	7	Nakamura and Steinsson (2014)
	Demand share of home state ϕ_H	$\frac{2}{3}+\frac{n}{3}$	Nakamura and Steinsson (2014)
firms	Labor cost share $1-\alpha$	0.65	Similar to Leeper, Traum and Walker (2017)
	Annual price persistence (sep. preferences) ξ	.735	Match defense multiplier (Ramey, 2011)
	same, GHH preferences	.629	
federal gov't	Federal debt-to-GDP $b_f/\bar{Y}$	0.70	Data
	Federal tax rate $\bar{\tau}_f$	0.22	Leeper, Traum and Walker (2017) data
	Federal IG transfers $\frac{\overline{IG}}{\bar{Y}}$	0.02	Data
	Federal government consumption and investment $\frac{\bar{G}_f}{\bar{Y}}$	0.12	Data
monetary authority	Interest rate smoothing ρ_r	0.75	Galí (2008)
	Reaction to inflation $\psi_{r,\pi}$	1.5	Galí (2008)
	Reaction to output $\psi_{r,y}$	$\frac{1}{2}$	Galí (2008), (annualized)
	Annual inflation rate $\bar{\Pi}$	2%	Inflation target
states	State government consumption $\frac{G_{st}}{\bar{Y}}$	0.08	Data
	State debt-to-GDP $\bar{b}_{st}/\bar{Y}$	0.075	Data
	Republican MPS ψ_{IG}	0	Consistent with Table 4 column (2)
	Democratic MPS ψ^*_{IG}	1.576	Implied by ψ_{IG} and Table 4 column (2)
	same, OLS estimate	.702	Implied by ψ_{IG} and Table 4 column (3)
	State tax rate $\bar{\tau}_{st}$	0.05	State marginal tax rate data
	State tax persistence ρ_τ	0.35	Match tax adjustment
	Reaction of state taxes to debt $\psi_{st,b}$	0.99	Determinacy
	Reaction of state taxes to net expenditure $\psi_{st,E}$	0.85	Match tax adjustment
IG	Persistence of fiscal shocks $\rho_{IG}=\rho_G=\rho_\tau$	0.63	2009 stimulus duration
	Standard deviation of IG shock ω_{IG}	0.30	2009 IG shock size

E.10 List of model equations

1. Exchange rate X_t

$$X_t = \left(\phi_H^* p_{Ht}^{1-\eta} + (1-\phi_H^*) p_{Ft}^{1-\eta}\right)^{\frac{1}{1-\eta}}$$

2. FFR R_t^n

$$R_t^n = (\bar{\Pi}/\beta)^{\rho_r} \left(\left(\frac{\bar{\Pi}_t}{\bar{\Pi}}\right)^{\psi_{r\pi}} \left(\frac{\bar{Y}_t}{\bar{Y}}\right)^{\psi_{ry}} \right)^{1-\rho_r}$$

3. Federal labor income tax rate τ_t^f

$$\begin{aligned}&(1-\gamma^f)((R_{t-1}^n - 1)\frac{b_{t-1}^f}{\Pi_t} - (\bar{R}^n - 1)\frac{\bar{b}^f}{\bar{\Pi}} + (n + (1-n)X_t^*)G_t^f - \bar{G}^f + ig_t - \overline{IG})\\ &= \tau_t^f (n w_t N_t + (1-n) w_t^* N_t^*) - \bar{\tau}^f \bar{w} \bar{N}\end{aligned}$$

4. Federal bond issuance b_t^f

$$(n + (1-n)X_t)G_t^f + \frac{IG_t}{P_t} + tr_t^f + \frac{R_{t-1}^n}{\Pi_t} b_{t-1}^f = \tau_t^f (n w_t N_t + (1-n) X_t w_t^* N_t^*) + b_t^f$$

5. Federal purchases G_t^f
   AR(1)

6. Federal IG transfers IG_t
   AR(1)

7. Federal transfers to agents tr_t^f
   constant

8. Aggregate inflation $\bar{\Pi}_t$

$$\bar{\Pi}_t = n\Pi_t + (1-n)\Pi_t^*$$

9. Aggregate output $\bar{Y}_t$

$$\bar{Y}_t = nY_t + (1-n)Y_t^*$$

10. Bond market clearing b_t.

$$b_t^f = n(b_t - b_t^{st}) + (1-n)(b_t^* - b_t^{st*})$$

11. Foreign budget constraint b_t^*

$$X_t C_t^{u*} + \frac{1}{\mu} b_t^* = (1 - \tau_t^f - \tau_t^{st*}) X_t w_t^* N_t^{u*} + \frac{1}{\mu} b_{t-1}^* \frac{R_{t-1}^n}{\Pi_t} + X_t \frac{Tr_t^{st*}}{P_t^*} + \frac{Tr_t^f}{P_t} + \frac{1 - (1-\mu)\kappa_{prc}}{\mu} X_t \left(Y_{F,t} - w_t^* N_t^*\right)$$

Symmetric

S1 Production function $\to N_t, N_t^*$

$$Y_{Ht} = A_t N_t^{1-\alpha}$$

Normalize $\bar{Y}_H = 1$. Then

$$\bar{A}_t = \bar{N}^{-(1-\alpha)}$$

S2 Stochastic discount factor M_t, M_t^*

$$M_t = \beta \frac{u_{c,t+1}}{u_{c,t}} \frac{1}{\Pi_{t+1}}$$

In steady state:

$$\bar{M}^n = \frac{\beta}{\bar{\Pi}}$$

S3 Marginal utility of income $\to C_t^u, C_t^{u*}$

$$u_c = C^{-1/\epsilon_c}$$

S4 Resource constraint $\to Y_{Ht}, Y_{Ft}$

$\phi_H^* < 1$ is equivalent to $(1 - \phi_H) < 1/n - 1$ or $2 < 1/n + \Phi_H$. For $n \leq \frac{1}{2}$, this assumption is always satisfied. This requires $\phi_H \geq \frac{2n-1}{n} \in (0, 1)$ for $n \in (0.5, 1)$.

$\phi_F = 1 - \phi_H, \phi_F^* = 1 - \phi_H^* = \frac{1-n-n(1-\phi_H)}{1-n}$.

$$(1-n) Y_{Ft} = \left(n\phi_F (C_t + G_t^{st}) + nG_t^f + (1-n)\phi_F^* (C_t^* + G_t^{st*}) X_t^\eta\right) \left(\frac{P_{Ft}}{P_t}\right)^{-\eta}$$

$$\begin{aligned} nY_{Ht} &= \left(n\phi_H (C_t + G_t^{st}) + nG_t^f + (1-n)\phi_H^* (C_t^* + G_t^{st*}) X_t^\eta\right) \left(\frac{P_{Ht}}{P_t}\right)^{-\eta} \\ &= \left(n\phi_H (C_t + G_t^{st}) + nG_t^f + n(1-\phi_H)(C_t^* + G_t^{st*}) X_t^\eta\right) \left(\frac{P_{Ht}}{P_t}\right)^{-\eta} \end{aligned}$$

using that $\phi_H^* = (1-\phi_H)\frac{n}{1-n}$. In the symmetric steady state:

$$\frac{\bar{C}}{\bar{Y}} = 1 - \frac{\bar{G}}{\bar{Y}}$$

S5 Constrained consumption C_t^c, C_t^{c*}

$$C_t^c = (1-(\tau_t^f + \tau_t^{st}))w_t N_t^c + tr_t + \kappa_{pr}^c (Y_{Ht} - w_t N_t)$$

In steady state:

$$\frac{\bar{C}^c}{\bar{Y}} = (1-\bar{\tau}^f - \bar{\tau}^{st})(1-\alpha)(1-1/\theta) + \frac{\overline{tr}}{\bar{Y}} + (1-(1-\alpha)(1-1/\theta))\kappa_{pr}^c$$

S6 Overall consumption C_t, C_t^*

$$C_t = \mu C_t^u + (1-\mu)C_t^c$$

S7 Labor supply N_t, N_t^*

$$N_t = \mu N_t^u + (1-\mu)N_t^c$$

Calibrated to $\bar{N} = \frac{1}{3}$

S8 Constrained labor supply N_t^c, N_t^{c*}

$$(1-\tau_t^f - \tau_t^{st})w_t = \kappa_N^c (N_t^c)^{1/\varepsilon_N}(C_t^c)^{1/\epsilon_C}$$

Implies κ_N^c

S9 Unconstrained labor supply N_t^u, N_t^{u*}
analogous as for constrained
Implies κ_N^u

S10 Bond Euler equation $\to u_{c,t}, u_{c,t}^*$

$$1 = \mathbb{E}_t\left[M_{t+1}^n\left(\frac{u_{b,t+1}}{u_{c,t+1}} + (R_t^n - \psi_{r,NFA}NFA_t)\right)\right],$$

where

$$\frac{u_b}{u_c} = \kappa_b b^{-1/\epsilon_b}(1-\kappa_G^u)\frac{(C^u)^{1/\epsilon_c}}{((1-\kappa_G^u) + \kappa_G^u(G^{st}/C^u)^{1-1/\lambda})^{\frac{1-\lambda/\epsilon_C}{\lambda-1}}}$$

Calibrate κ_b to match $\bar{b} = \bar{b}^f + \bar{b}^{st}$.

S11 Relative producer prices $p_{H,t}, p_{F,t}$

$$1 = \left(\phi_H p_{Ht}^{1-\eta} + (1-\phi_H) p_{Ft}^{1-\eta}\right)^{\frac{1}{1-\eta}}$$

$$p_{H,t} = p_{H,t-1} \frac{\Pi_{H,t}}{\Pi_t}$$

In steady state, relative prices are unity.

S12 Real wages w_t, w_t^*

$$\begin{aligned} w_t &= (1-\alpha) \frac{y_{Ht}}{N_t} mc_{ht}^r \\ &= \frac{1-\alpha}{\alpha} \frac{K_t^e}{N_t} r_t^{k,r} \end{aligned}$$

In steady state:

$$\bar{w} = (1-\alpha)(1-1/\theta) \frac{1}{\bar{N}},$$

using that steady state output is unity.

S13 State transfers tr_t^{st}, tr_t^{st*}
constant

S14 State debt issuance b_t^{st}, b_t^{st*}

$$G_t^{st} + tr_t^{st} + \frac{R_{t-1}^n}{\Pi_t} b_{t-1}^{st} = b_t^{st} + \frac{IG_t}{P_t} + \tau_t^{st} w_t N_t.$$

and

$$X_t G_t^{st*} + X_t tr_t^{st*} + \frac{R_{t-1}^n}{\Pi_t} b_{t-1}^{st} = b_t^{st} + X_t \frac{IG_t}{P_t} + X_t \tau_t^{st} w_t^* N_t^*.$$

Calibrate debt, set transfers in steady state:

$$\frac{\overline{tr}^{st}}{\bar{Y}} = \bar{\tau}^{st}(1-\alpha)\left(1-\frac{1}{\theta}\right) - \left(\frac{\bar{R}_n}{\bar{\Pi}} - 1\right)\frac{\bar{b}^{st}}{\bar{Y}} - \frac{\bar{G}^{st}}{\bar{Y}}$$

S15 State labor income tax rate $\tau_t^{st}, \tau_t^{st*}$

$$(1-\gamma^s)((R_{t-1}^n - 1)\frac{b_{t-1}^{st}}{\Pi_t} - (\bar{R}^n - 1)\frac{\bar{b}^{st}}{\bar{\Pi}}) + G_t^{st} - \bar{G}_t^{st} - (\frac{IG_t}{P_t} - \bar{I}G)+) = \tau_t^{st} w_t N_t - \bar{\tau}^{st} \bar{W} \bar{N}.$$

Calibrated

S16 State government spending G_t^{st}, G_t^{st*}

$$G_{st,t} = \psi_{IG}(\frac{IG_t}{P_t} - \bar{I}G) + G^x_{st,t}$$

S17 Exogenous state government spending $G^{st}_{x,t}, G^{st*}_{x,t}$

$$G^x_{st,t} = (1-\rho_{st,g})\bar{G}^{st} + \rho_{st,g} G^x_{st,t-1} + \omega_{st,g}\epsilon^x_{st,t}$$

S18 Producer price inflation Π_{Ht}, Π_{Ft}

$$\Pi_{Ht}^{1-\theta} = (1-\xi)\left(\frac{p_{ht}}{p_{Ht}}\Pi_{H,t}\right)^{1-\theta} + \xi\bar{\Pi}^{1-\theta} \quad \Leftrightarrow \quad 1 = (1-\xi)\left(\frac{p_{ht}}{p_{Ht}}\right)^{1-\theta} + \xi\left(\frac{\bar{\Pi}}{\Pi_{H,t}}\right)^{1-\theta}$$
$$\Pi_{Ft}^{1-\theta} = (1-\xi)\left(\frac{p_{ft}}{p_{Ft}}\Pi_{F,t}\right)^{1-\theta} + \xi\bar{\Pi}^{1-\theta} \quad \Leftrightarrow \quad 1 = (1-\xi)\left(\frac{p_{ft}}{p_{Ft}}\right)^{1-\theta} + \xi\left(\frac{\bar{\Pi}}{\Pi_{F,t}}\right)^{1-\theta}$$

In steady state, $\Pi_H = \Pi_F = \bar{\Pi}$.

$$p_{ht}(z) \equiv \frac{P_{ht}(z)}{P_t} = \frac{\theta}{\theta-1}\frac{CN_t}{CD_t},$$
$$p_{ft}(z) \equiv \frac{P_{ft}(z)}{P_t} = \frac{\theta}{\theta-1}\frac{CN_t^*}{CD_t^*}$$

Flex price:

$$1 = \frac{p_{ht}}{p_{Ht}}$$
$$1 = \frac{p_{ft}}{p_{Ft}}$$
$$p_{ht}(z) \equiv \frac{P_{ht}(z)}{P_t} = \frac{\theta}{\theta-1}\frac{CN_t}{CD_t} = \frac{\theta}{\theta-1}MC_t^r$$
$$p_{ft}(z) \equiv \frac{P_{ft}(z)}{P_t} = \frac{\theta}{\theta-1}\frac{CN_t^*}{CD_t^*} = \frac{\theta}{\theta-1}MC_t^{r*}$$

S19 State inflation Π_t, Π_t^*

$$\left(\frac{P_t^*}{P_{t-1}^*}\right)^{1-\eta} = \phi_H^* \frac{P_{Ht}^{1-\eta}}{\phi_H^* P_{H,t-1}^{1-\eta} + (1-\phi_H^*)P_{F,t-1}^{1-\eta}} + (1-\phi_H^*)\frac{P_{Ft}^{1-\eta}}{\phi_H^* P_{H,t-1}^{1-\eta} + (1-\phi_H^*)P_{F,t-1}^{1-\eta}}$$
$$\Leftrightarrow (\Pi_t^*)^{1-\eta} = \phi_H^* \frac{\Pi_{Ht}^{1-\eta}}{\phi_H^* + (1-\phi_H^*)(p_{F,t-1}/p_{H,t-1})^{1-\eta}} + (1-\phi_H^*)\frac{\Pi_{Ft}^{1-\eta}}{\phi_H^*(p_{H,t-1}/p_{F,t-1})^{1-\eta} + (1-\phi_H^*)}$$
$$\Pi_t = \Pi_t^* \frac{X_{t-1}}{X_t}.$$

$$\hat{\pi}_t = \phi_H \hat{\pi}_{H,t} + (1-\phi_H)\hat{\pi}_{F,t}$$
$$\hat{\pi}^*_t = \phi^*_H \hat{\pi}_{H,t} + (1-\phi^*_H)\hat{\pi}_{F,t}$$

S20 Calvo denominators CD_t, CD^*_t

$$CD_t = Y_{Ht} + \mathbb{E}_t[M^n_{t,t+1}\bar{\Pi}^{1-\theta}\xi CD_{t+1}].$$

In steady state:

$$\overline{CD} = \frac{\bar{Y}_H}{1-\beta\xi\bar{\Pi}^{-\theta}}$$

Flex-price:

$$CD_t = Y_{Ht}$$

S21 Calvo (real) numerators CN_t, CN^*_t

$$CN_t = Y_{H,t}MC^r_t + \mathbb{E}_t[M^n_{t,t+1}\Pi_{t+1}\bar{\Pi}^{-\theta}\xi CN_{t+1}]$$
$$CN^*_t = Y_{F,t}MC^{r*}_t + \mathbb{E}_t[M^{n*}_{t,t+1}\Pi_{t+1}\bar{\Pi}^{-\theta}\xi CN^*_{t+1}]$$

In steady state:

$$\overline{CN} = \frac{\bar{Y}_H}{1-\beta\xi\bar{\Pi}^{-\theta}}\left(1-\frac{1}{\theta}\right)$$

Flex-price

$$CN_t = Y_{H,t}MC^r_t$$
$$CN^*_t = Y_{F,t}MC^{r*}_t$$