Supplemental Information, "When Mayors Matter"

Descriptive Statistics

Tables SI1 and SI2 report descriptive statistics for our independent and dependent variables, respectively.

Tables SI1 and SI2 Here

Robustness Checks

Here, we report additional tests conducted to confirm that our main results are not sensitive to specific analysis decisions.

1) *Multiple imputation*. To investigate the consequences of using multiple imputation to recover missing values on a few variables, we replicated the models deleting the eight observations that are not fully observed. Doing so, we estimate an impact of -2.43 (SE=0.88) for a Democratic victory on police protection and an impact of -0.89 percentage points (SE=0.55) on fire protection. Using simulation, we calculate the probability that this police spending coefficient is positive to be less than 0.01. For fire spending, the two-sided p-value is 0.08. Based on this test, we conclude that our use of multiple imputation to recover missing values does not substantially affect our results.

2) *Outliers*. To ensure that the results are not driven by outliers, we re-estimate our baseline models dropping every observation in turn. For spending on the police, every one of the resulting 134 data sets indicates a substantively and statistically significant impact of

partisanship. For fire protection, only one of the possible data sets produces a borderline-insignificant result (p=.14, two-sided test). This test provides greater confidence that “unusual” observations are not driving our main results.

3) *Observations far from the discontinuity*. To test whether our results are being driven by observations far from the discontinuity, we remove 30 observations where the winner received over 75% of the vote or less than 25% of the vote. We then re-estimate the full model for each dependent variable. For policing and fire protection, the results remain stable. Under this model, the election of a Democratic mayor leads to a 2.3 percentage point drop in the share of spending devoted to the police (SE=1.1), and a 0.7 percentage point drop in the share of spending devoted to fire protection (SE=0.6). In this specification, we also get another hint of where Democrats might be spending more compared to Republicans: spending on housing increases in this model by 1.6 percentage points (SE=0.8). For other spending areas, and for all revenue measures, we see no strong impacts, as in the original analyses.

4) *Size of window*. To further explore how sensitive our results are to the inclusion of observations far away from the discontinuity, we vary the “window” or range of observations around the discontinuity that we include in the analyses. Recommended by Imbens and Lemieux (2007) and Green et al. (2009), this can also be referred to as varying the bandwidth of a rectangular kernel density. By focusing on the observations closest to the discontinuity, we reduce model dependence, but also are likely to increase our standard errors. A window size of 0.08 means that we include only those observations where the Democrat wins between 46% and 54% of the vote. Put differently, if the window size is 0.08, the winner’s share of the two-candidate vote can be no more than 8 percentage points larger than the loser’s share. We then

estimate the impact of a narrow Democratic victory using the model from Tables 1, and present those estimates as a dot along with a line indicating its 95% confidence interval in the article's Figure 3.[1] As the window size increases, the confidence intervals decline since we are using more data. But the critical point is that our results are quite robust to how we specify the window. For all possible windows, the impact of a Democrat winning on police spending is negative, and it is almost always statistically significant, even using two-sided tests. In fact, we even detect a substantively and statistically significant police spending decline of 6.1 percentage points when using the 34 observations within the 0.08 window (p=.10, two-sided). The impact of a Democrat winning on fire spending is negative and is typically significant as well.

5) *Inclusion of covariates*. On its own, the discontinuity design should eliminate the threat of omitted variable bias. However, the possibility of covariate imbalances arising by chance or because of a violation of the RDD assumptions makes it valuable to evaluate the possibility that omitted variables are biasing our results. We therefore re-estimate our models conditional on each of 35 covariates, inserting each new covariate into the basic model one at a time.[2] These variables include the crime rate, population density, residential turnover, region, percent immigrant, change in the city's population, race of the mayor, whether the election brought about a partisan change, whether the victor was an incumbent, and many others. Figure SI1 shows how stable our estimate of a Democrats' impact on policing is to a wide range of potentially omitted variables. Starting from the baseline model of the change in police spending, it presents the

[1] As the sample sizes decline, so does the utility of clustering standard errors by city. For the smallest window sizes of 20%, 16%, 12% and 8%, the standard errors are not clustered.

[2] These analyses use fixed demographic measures derived from the Census, such as the logged 1990 population. Across major U.S. cities, 1990 demographics and 2000 demographics are typically very highly correlated. For instance, the correlation for logged population is 0.986 and for logged median household income it is 0.944. Given such high correlations, it is not surprising that the robustness to omitted variables also holds if we use linear interpolation to estimate time-varying demographic measures.

estimated impact when the named variable is added to the model. In no case does the inclusion of the omitted variable substantially change the estimated impact of electing a Democrat on anti-crime spending. Our core result does not appear to be a product of differing demographics, institutions, or political contexts between the cities that narrowly elect Democrats and those that do not.

Figure SI1 Here

To further explore whether any of the potential covariates are imbalanced at the point of the discontinuity (and hence likely to introduce bias due to their omission in our main analyses), in Figure SI2 we explore baseline covariate differences by using the basic model with only the various functions of the percent voting Democratic as independent variables.[3] For each of the 35 covariates employed above, and also for the seven covariates that make up the baseline model, we estimate the "impact" of a Democratic mayor on the covariate in question. Since the covariates are all pre-treatment, these are placebo tests: we should not expect to find any strong relationships except by chance. And indeed, we do not, as Figure SI2 makes clear. Treating each potentially omitted variable as a dependent variable, it presents the change in that variable across the discontinuity. On all but two variables, cities where Democrats just win are statistically indistinguishable from cities where Democrats just lose. Cities that narrowly elect a Democrat are more likely to have home rule, and more likely to have smaller populations. Still, we know from Figure SI1 that conditioning on these chance imbalances does not impact our estimated treatment effect.

Figure SI2 Here

[3] In this case, the conservative option is to *not* adjust the standard errors for clustering, so we do not, although this choice makes little impact on the substantive results.

6) *Effects of local political institutions and state politics*. The article demonstrates the moderating impact of electoral institutions. Here, we consider other local political factors that might moderate partisanship's impact, including mayor-council structures, home rule, and larger city councils. We also consider state-level factors, such as whether the lower statehouse chamber is controlled by Democrats, whether the upper statehouse chamber is controlled by Democrats, or whether the governor is a Republican. We do not find a detectably different impact of mayoral partisanship in the presence of these local political institutions or state-level partisan environments. Rather, we conclude that the key institutional moderator is electoral: in cities where elections are formally partisan, policymaking appears to have partisan antecedents as well.

7) *Time after election*. We estimate changes from the baseline election year to the second subsequent fiscal year instead of the third. Doing so largely confirms the patterns identified above, with policing (-1.61 percentage points, SE=0.70) and fire (-1.09 percentage points, SE=0.46) both reduced under Democrats. Since these measures cover only two years, it makes sense that the impact on policing is smaller in size. By contrast, looking at changes over only the first fiscal year is essentially a placebo test; these budget decisions are largely made during the previous administration and so newly elected mayors have few opportunities to influence these outcomes. As expected, this placebo test produces no significant impacts of a narrow Democratic victory on fire or police spending.

8) *Effect of post-9/11 changes in federal grants to cities*. The core results also appear when we consider only pre-2002 elections, ruling out the concern that these effects are a product of differential post-September 11th federal grants.

9) *Exclusion of races against independents*. Candidates running for mayor who are not affiliated with one of the major parties could include both people to the right of the Democratic candidate and people to the left. As one might expect, our main result increases slightly when we drop the 26 cases where the opponent was not a Republican, to 2.6 percentage points. The 95% confidence interval runs from 0.7 percentage points to 4.5 percentage points. Nor does this result depend on the covariates: when the model includes only the various measures of the percent voting for the Democrat, it returns an impact of 2.0 percentage points with a 95% confidence interval from 0.2 percentage points to 3.9 percentage points.

Comparison with Ferreira and Gyourko (2009)

With a data set that covers more cities over a longer period of time, Ferreira and Gyourko (2009) conclude that partisanship is *not* a strong influence on cities' fiscal patterns. This section uses that data set alongside our own to explore why the results differ.

Merging Ferreira and Gyourko's data set with the city financial data available to us, we create a data set with 925 observed elections where a Democratic mayor runs against a non-Democratic mayor. The elections span the period from 1972 to 2004, with the median observed election falling in 1989. These elections come from 289 unique U.S. cities. We use our paper's specification of the dependent variable, which considers the change in the spending share devoted to the police in the three fiscal years subsequent to the election.

Using our smaller data set of 134 observations, we found that an OLS model which only includes various functions of the forcing variable and an indicator for a Democratic victory recovers an estimated treatment effect of 2.0 percentage points, with a 95% confidence interval from 0.2 to 3.9 percentage points.[4] On average, cities that elect a Democratic mayor are spending 2.0 percentage points less fighting crime than comparable cities that elect a Republican. This effect is shown at the bottom of Figure SI3. With the data on urban elections collected by Ferreira and Gyourko (2009), by contrast, the same model generates an estimated impact of 0.1 percentage point, with a tighter 95% confidence interval from -0.9 percentage points to 1.1 percentage points. The null result using their data on elections is shown as the first line in Figure SI3, with the surrounding line indicating the 95% confidence interval.

Figure SI3 Here

One possible explanation for the discrepancy is that the impact of Democratic mayors might have shifted over time. We thus re-estimated the same model only for the 416 observed elections after 1989, which marked the beginning year for our data set. In Figure SI3, this result is labeled "Same Years." Here, we estimate the impact to be *positive*, at 0.98 percentage points, with a 95% confidence interval from -0.4 percentage points to 2.5 percentage points. Variation over time does not explain the discrepancy.

The two data sets also differ in their sampling frames. Ferreira and Gyourko contacted all cities with a 2000 population above 25,000, while our data set is restricted to cities above 170,000 people. We thus reduced the Ferreira and Gyourko data to the set of 158 elections that were observed in any year in cities within our sampling frame. Here, we again estimate an

[4] Specifically, this model has seven covariates: whether the Democratic candidate wins, the share of the city voting Democratic, the squared share voting Democratic, the cubed share voting Democratic, and interactions with the three functions of the forcing variable allowing for different coefficients on either side of the discontinuity.

impact that is very nearly zero, as shown by the impact labeled “Same Cities.” This suggests that city size alone does not account for the difference either.

As a next step, we combined the previous experiments by reducing their election data to the 74 observations that are from both the cities in our sample and the years covered by our sample. This produces an estimated impact of -0.98 percentage points, an impact which is negative in 78% of simulations. Yet even here, we should keep in mind that the two data sets used different methods of data collection, with our data relying exclusively on publicly available information about partisanship. Given that fact, and given the finding above that the impact of partisanship is strongest in cities with partisan elections, we might suspect that our finding of a notable partisan impact is driven by cases where the partisanship of both candidates is publicly known. Reducing the Ferreira and Gyourko data set to the actual elections that are common to both data sets reinforces this interpretation. In those 49 elections, we recover an estimated treatment effect of 2.3 percentage points, with a wide 95% confidence interval from -6.1 percentage points to 1.5 percentage points. Even in this small data set, simulations indicate that the probability that the effect of a Democratic mayor is negative is 0.88. That number does not reach conventional levels of statistical significance. But the point estimate is now very similar to those recovered through our data set, and the substantive conclusion is as well. Given these results, it seems quite plausible that data collection strategies matter: *by analyzing cities where partisanship was publicly known, our data set focuses on cases where it has the potential to be a meaningful signal.*

Supplemental Information

Table 1: Descriptive Statistics, Independent variables, 134 city elections.

Variable	Mean	SD	Min.	Max.
Democrat Wins	0.672	0.471	0.000	1.000
% Voting Democratic	0.573	0.175	0.185	0.946
Incumbent	0.455	0.500	0.000	1.000
Partisan Election	0.413	0.494	0.000	1.000
Change in Party	0.159	0.367	0.000	1.000
Party on Ballot	0.602	0.492	0.000	1.000
Black Winner	0.231	0.423	0.000	1.000
Black Loser	0.222	0.417	0.000	1.000
Dem. Share, Upper House	0.546	0.500	0.000	1.000
Dem. Share, Lower House	0.700	0.460	0.000	1.000
GOP Governor	0.511	0.502	0.000	1.000
Council % Black	0.196	0.157	0.000	0.632
Council Size	11.848	7.637	4.000	50.000
Home Rule	0.720	0.451	0.000	1.000
Mayor-Council	0.644	0.481	0.000	1.000
Council-Manager	0.326	0.470	0.000	1.000
% At Large	0.393	0.409	0.000	1.000
Crime Rate 91	10291.165	3047.362	4361.000	18953.000
Change, Crime Rate 91-99	-2581.943	1950.610	-7670.000	6906.000
Pop. Density 90	1.724	1.613	0.051	9.151
% with Bachelor's Degree 90	0.242	0.074	0.081	0.528
% Same House 85-90	0.490	0.077	0.334	0.672
% on Public Assistance 90	0.090	0.040	0.024	0.219
% on Social Security 90	0.236	0.052	0.093	0.345
% Homeowner 90	0.511	0.081	0.287	0.730
% Poor 90	0.176	0.056	0.064	0.312
Median Home Price 90	86048.507	60072.990	40400.000	350800.000
Average Commute 90	21.586	4.057	15.600	36.500
South	0.425	0.496	0.000	1.000
West	0.172	0.378	0.000	1.000
Northeast	0.104	0.307	0.000	1.000
Homogeneity 90	0.505	0.107	0.315	0.901
% Hispanic 90	0.108	0.148	0.004	0.689
Change, Log Median Income 90-00	0.329	0.069	0.171	0.519
% Immigrant 90	0.086	0.094	0.010	0.597
Change, Log Population 90-00	0.106	0.140	-0.130	0.617
Change, % Black 90-00	0.010	0.036	-0.059	0.148

Continued ...

Table 1 – Continued

Variable	Mean	SD	Min.	Max.
Federal aid per capita	0.146	0.339	0.001	2.676
Independent Loses	0.194	0.397	0.000	1.000
December Fiscal Year	0.250	0.435	0.000	1.000
Log Population 90	13.019	0.839	11.611	15.806
% Black 90	0.268	0.172	0.006	0.668
Log Med Income 90	10.194	0.203	9.737	10.939
Intergov't Revenue per Cap.	0.501	0.611	0.036	2.991

	Mean	SD	Min	Max	Intergov't
Policing	0.110	0.040	0.000	0.231	
Fire	0.063	0.030	0.000	0.146	
Roads	0.064	0.039	0.000	0.223	0.328
Parks	0.055	0.035	0.000	0.193	
Housing	0.039	0.029	0.000	0.168	0.807
Sanitation	0.033	0.019	0.000	0.107	0.012
Health	0.021	0.024	0.000	0.150	0.267
Administration	0.014	0.012	0.000	0.095	
Libraries	0.007	0.009	0.000	0.038	
Inspection	0.007	0.007	0.000	0.038	
Natural Resources	0.003	0.007	0.000	0.043	
Taxes / Total Revenues	0.466	0.141	0.156	0.826	
Sales Tax Share	0.198	0.226	0.000	0.796	
Property Tax Share	0.464	0.247	0.050	0.906	
Log, Total Taxes	12.600	1.197	8.089	16.976	
Total Taxes Per Capita	750	717	18	5,318	
Police Employees	2,814	6,801	44	50,673	
Share, Police Employees	0.164	0.059	0.017	0.345	
Share, Police Pay	0.211	0.066	0.018	0.328	

Table 2: Descriptive Statistics, Dependent Variables, 134 Elections.

	β	SE
Intercept	0.018	0.109
Democrat Wins	0.138	0.316
Pct Dem	-0.897	0.932
Pct Dem Squared	2.292	2.775
Pct Dem Cubed	-1.803	2.629
Independent Loses	-0.001	0.002
December FY	0.002	0.003
Logged 1990 Pop.	-0.002	0.001
Pct Black 90	-0.015	0.006
Logged Median Income 90	0.012	0.008
Intergovernmental Revenue per Capita	0.000	0.002
Democrat wins x Pct Democrat	-0.267	1.621
Democrat wins x Pct Democrat Squared	-0.509	3.406
Democrat wins x Pct Democrat Cubed	0.921	2.817

Table 3: OLS Estimates, DV=Changes in the Share of Spending on Fire, 134 City Elections.

Table 4: Full list of U.S. city elections.

Number	City	Year	% Dem.	Δ Police	Name
1	DC, Washington	1990	0.88	-0.01	Sharon Pratt Dixon
2	DC, Washington	1994	0.57	0	Marion Barry
3	DC, Washington	1998	0.69	0.01	Anthony Williams
4	MD, Baltimore	1991	0.72	0.01	Kurt Schmoke
5	MD, Baltimore	1995	0.79	0	Kurt Schmoke
6	MD, Baltimore	1999	0.9	0.01	Martin O'Malley
7	MD, Baltimore	2004	0.88		Martin O'Malley
8	NY, Buffalo	1993	0.79	-0.01	Anthony Masiello
9	NY, New York	1993	0.49	0.01	Rudolph Giuliani
10	NY, New York	1997	0.44	0	Rudolph Giuliani
11	NY, New York	2001	0.49	-0.01	Michael Bloomberg
12	NY, Rochester	1993	0.79	0	William Johnson, Jr.
13	NY, Yonkers	1991	0.52	0.02	Terence Zaleski
14	NY, Yonkers	1995	0.43		John Spencer
15	NY, Yonkers	2003	0.41	0	Phil Amicone
16	PA, Philadelphia	1991	0.68	-0.01	Ed Rendell
17	PA, Philadelphia	1995	0.79	0	Ed Rendell
18	PA, Philadelphia	1999	0.51	0	John Street
19	PA, Philadelphia	2003	0.59	-0.01	John Street
20	PA, Pittsburgh	1993	0.81	-0.02	Tom Murphy
21	PA, Pittsburgh	2001	0.76	0.01	Tom Murphy
22	VA, Chesapeake	1996	0.55	0	William Ward
23	IL, Chicago	2003	0.85	-0.01	Richard Daley
24	IN, Fort Wayne	1999	0.5	-0.04	Graham Richard
25	IN, Fort Wayne	2003	0.58	-0.02	Graham Richard
26	IN, Indianapolis city	1991	0.42	-0.02	Stephen Goldsmith
27	IN, Indianapolis city	1995	0.38	0	Stephen Goldsmith
28	IN, Indianapolis city	1999	0.55	-0.01	Bart Peterson
29	IN, Indianapolis city	2003	0.63	-0.01	Bart Peterson
30	KY, Louisville	2002	0.75	0.04	Jerry Abramson
31	MN, Minneapolis	1997	0.55	0.02	Sharon Sayles Belton
32	MO, Kansas City	2003	0.6	-0.03	Kay Barnes
33	MO, St. Louis	1993	0.79	0.02	Freeman Bosley, Jr.
34	MO, St. Louis	1997	0.76	-0.01	Clarence Harmon
35	MO, St. Louis	2001	0.88	0.01	Francis Slay
36	OH, Akron	2003	0.71	0.03	Donald Plusquellic
37	OH, Cincinnati	1991	0.51	-0.01	Dwight Tillery
38	OH, Cincinnati	1995	0.51	0.01	Roxanne Qualls
39	OH, Cleveland	1993	0.84	0	Michael White
40	OH, Columbus	1991	0.48	0.01	Greg Lashutka

Continued ...

Table 4 – Continued

Number	City	Year	% Dem.	Δ Police	Name
41	OH, Columbus	1995	0.32	0.01	Greg Lashutka
42	OH, Columbus	1999	0.6	0	Michael Coleman
43	OH, Toledo	1993	0.5	0.01	Carty Finkbeiner
44	OH, Toledo	1997	0.51	0.02	Carty Finkbeiner
45	AL, Montgomery	1999	0.54	-0.01	Bobby Bright
46	AR, Little Rock	1994	0.82	0.02	Jim Dailey
47	AR, Little Rock	1998	0.9	0	Jim Dailey
48	AR, Little Rock	2002	0.85	0.01	Jim Dailey
49	FL, Jacksonville	1995	0.49	0.01	John Delaney
50	FL, Jacksonville	2003	0.42	0.01	John Peyton
51	FL, Miami	1993	0.59	-0.04	Stephen Clark
52	FL, Orlando	2004	0.63		Buddy Dyer
53	GA, Atlanta	1993	0.73	-0.02	Bill Campbell
54	GA, Atlanta	1997	0.53	-0.01	Bill Campbell
55	GA, Atlanta	2001	0.6	-0.01	Shirley Franklin
56	LA, Baton Rouge	1992	0.2	0	Ed McHugh
57	LA, Baton Rouge	1996	0.34	0	Ed McHugh
58	LA, Baton Rouge	2000	0.43	0.01	Bobby Simpson
59	LA, Baton Rouge	2004	0.54		Melvin Kip Holden
60	LA, Shreveport	1990	0.41	0.01	Hazel Beard
61	LA, Shreveport	1994	0.41	0.01	Robert Bo Williams
62	LA, Shreveport	1998	0.6	-0.03	Keith Hightower
63	LA, Shreveport	2002	0.75	0	Keith Hightower
64	MS, Jackson	1997	0.18	-0.01	Harvey Johnson, Jr.
65	MS, Jackson	2001	0.61	0.01	Harvey Johnson, Jr.
66	NC, Charlotte	1991	0.47	0.03	Richard Vinroot
67	NC, Charlotte	1993	0.33	0.09	Richard Vinroot
68	NC, Charlotte	1995	0.38	0.04	Patrick McCrory
69	NC, Charlotte	1997	0.22	0	Patrick McCrory
70	NC, Charlotte	1999	0.39	0.01	Patrick McCrory
71	NC, Charlotte	2001	0.33	-0.01	Patrick McCrory
72	NC, Charlotte	2003	0.41	-0.03	Patrick McCrory
73	NC, Raleigh	1995	0.4	-0.01	Thomas Fetzer
74	NC, Raleigh	1997	0.42	0.01	Thomas Fetzer
75	NC, Raleigh	1999	0.5	0.04	Paul Coble
76	NC, Raleigh	2001	0.51	0	Charles Meeker
77	NC, Raleigh	2003	0.59	-0.02	Charles Meeker
78	NC, Winston-Salem	1997	0.43	0.01	Jack Cavanagh, Jr.
79	NC, Winston-Salem	2001	0.78	0	Allen Joines
80	OK, Oklahoma City	2002	0.26	0	Kirk Humphreys
81	OK, Tulsa	1990	0.67	0.02	Rodger Randle

Continued . . .

Table 4 – Continued

Number	City	Year	% Dem.	Δ Police	Name
82	OK, Tulsa	1994	0.59	-0.01	Susan Savage
83	OK, Tulsa	1998	0.54	0	Susan Savage
84	OK, Tulsa	2002	0.36	-0.03	Bill LaFortune
85	TN, Knoxville	1999	0.35	0.03	Victor Ashe
86	TN, Memphis	1995	0.75	0.02	Willie Herenton
87	TN, Memphis	2003	0.74	0	Willie Herenton
88	TX, Austin	1997	0.55	0	Kirk Watson
89	TX, Austin	2000	0.92	0.02	Kirk Watson
90	TX, Austin	2001	0.78	0.02	Gus Garcia
91	TX, Dallas	1991	0.33	-0.05	Steve Bartlett
92	TX, Dallas	1995	0.73	0.01	Ron Kirk
93	TX, Dallas	2002	0.55	-0.01	Laura Miller
94	TX, Dallas	2003	0.59	0.01	Laura Miller
95	TX, El Paso	1995	0.27	0.03	Larry Francis
96	TX, El Paso	2001	0.63	-0.01	Raymond Caballero
97	TX, Houston	1991	0.53	0	Bob Lanier
98	TX, Houston	1993	0.95	-0.01	Bob Lanier
99	TX, Houston	1995	0.9	-0.01	Bob Lanier
100	TX, Houston	1997	0.53	0	Lee Brown
101	TX, Houston	1999	0.74	0	Lee Brown
102	TX, Houston	2001	0.52	-0.01	Lee Brown
103	TX, Houston	2003	0.63	-0.02	Bill White
104	TX, San Antonio	1995	0.47	0.01	William Thornton
105	TX, San Antonio	1997	0.43	-0.01	Howard Peak
106	AK, Anchorage	2000	0.66	0.01	Mark Begich
107	AK, Anchorage	2003	0.55	0	Mark Begich
108	AZ, Tucson	1991	0.56	0.01	George Miller
109	AZ, Tucson	1995	0.61	0.01	George Miller
110	AZ, Tucson	1999	0.42	0.02	Robert Walkup
111	AZ, Tucson	2003	0.49	0.04	Robert Walkup
112	CA, Fresno	2000	0.39	0.02	Alan Autry
113	CA, Irvine	2002	0.53	0.04	Larry Agran
114	CA, Irvine	2004	0.52		Beth Krom
115	CA, Los Angeles	1993	0.46	0.01	Richard Riordan
116	CA, Los Angeles	1997	0.36	0	Richard Riordan
117	CA, Sacramento	2004	0.74		Heather Fargo
118	CA, San Francisco	2003	0.53	-0.01	Gavin Newsom
119	CA, San Jose	1998	0.51	-0.01	Ron Gonzales
120	CA, San Jose	2002	0.81	0	Ron Gonzales
121	CO, Denver	1999	0.92	-0.01	Wellington Webb
122	HI, Honolulu	1992	0.49	-0.01	Frank Fasi

Continued ...

Table 4 – Continued

Number	City	Year	% Dem.	Δ Police	Name
123	ID, Boise City	2003	0.67	0.04	David Bieter
124	KS, Wichita	2003	0.23	-0.01	Carlos Mayans
125	NE, Lincoln	2003	0.51	-0.01	Coleen Seng
126	NE, Omaha	1994	0.43	0.01	Hal Daub
127	NE, Omaha	1997	0.5	0.01	Hal Daub
128	NE, Omaha	2001	0.51	-0.04	Mike Fahey
129	NM, Albuquerque	1993	0.5	0	Martin Chavez
130	NM, Albuquerque	1997	0.54	0.03	Jim Baca
131	NM, Albuquerque	2001	0.52	0	Martin Chavez
132	NV, Las Vegas	1999	0.64	0.01	Oscar Goodman
133	NV, Las Vegas	2003	0.94	0	Oscar Goodman
134	WA, Seattle	1993	0.57	-0.01	Norman Rice

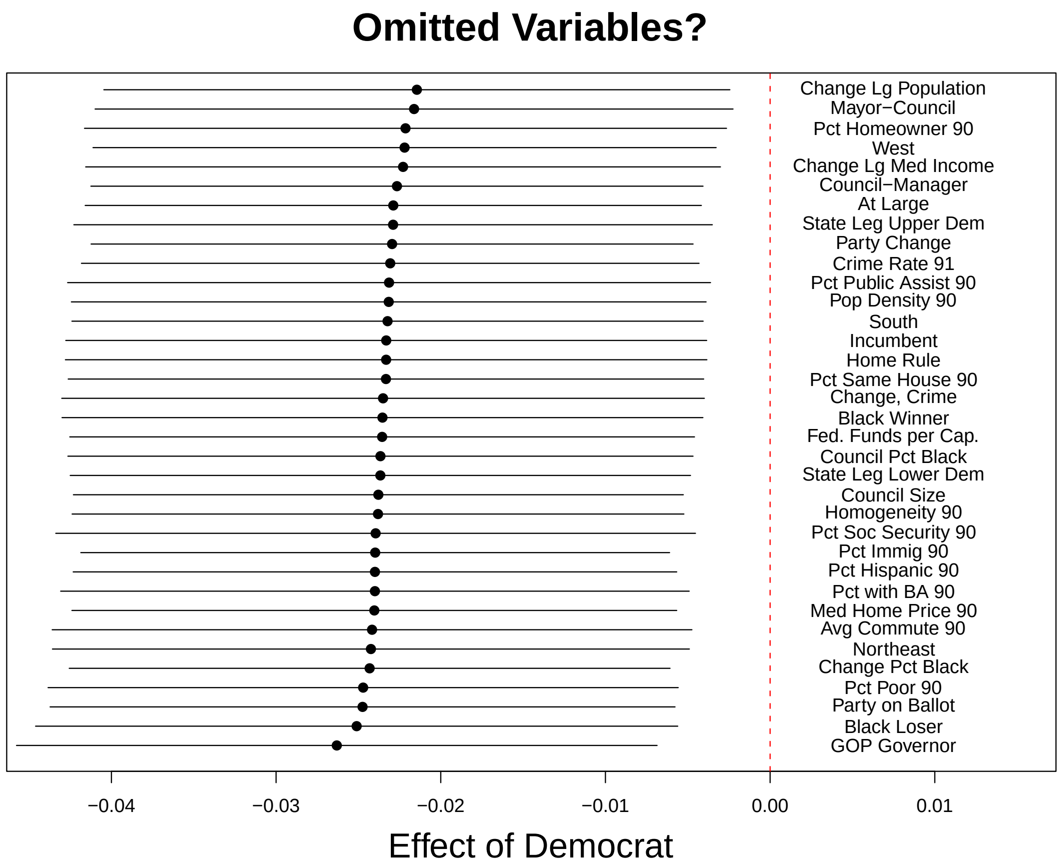

Figure 1: OLS Estimates, Effect of a Democratic Victory on Police Spending. *Conditional on the inclusion of potential confounding variables.*

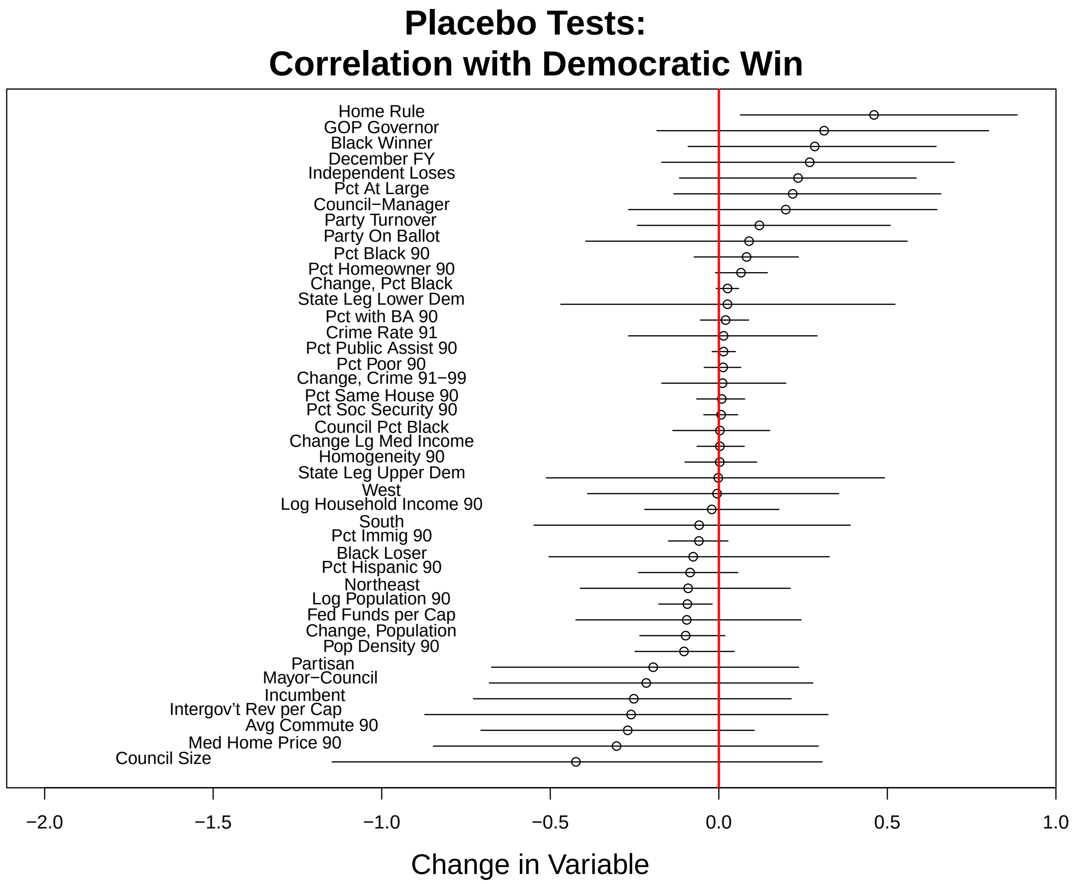

Figure 2: OLS Estimates, Placebo Tests, DV=Covariates, IV=Democratic Victory.

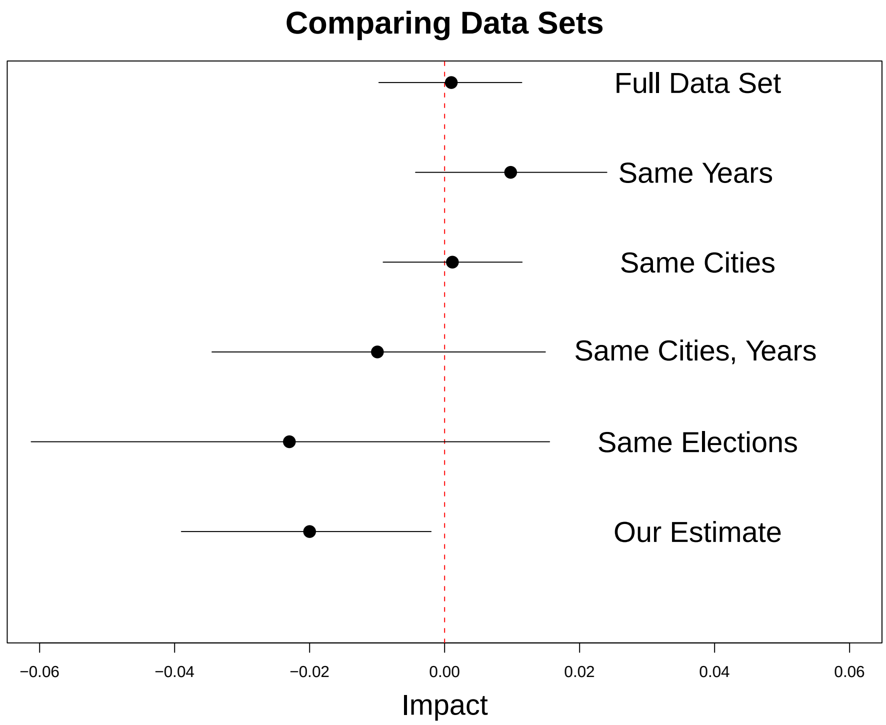

Figure 3: OLS Estimates, IV=Democratic Victory, Comparisons with Ferriera and Gyourko (2009)'s data set. *The dependent variable is the change in the three-year share of expenditures on the police. The models include only the percent Democratic, an indictor for a Democratic victory, and various functions of those variables.*