Machine Politics in Chicago's Menu Program*

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Abstract

In numerous urban political systems, the reality of patronage clashes with theoretical predictions that marginal voters determine policy outcomes. This paper examines the role of patronage using novel data from Chicago's menu program, where city council members distribute public goods in their wards using a $1.5M budget. I start with the case of Alderman Bernie Stone, whom citizens alleged of under-providing precincts where he lost. I find strong evidence of a spending shift towards his opponents from his supporters after his removal from office. Next, I investigate if this is a broader issue using two difference-in-differences approaches. I find no significant shift comparing incumbent aldermen who barely won and lost reelection. Comparing indicted aldermen to "entrenched" aldermen shows a notable spending shift, albeit the results are sensitive. The top eight Precincts that supported an indicted alderman saw a 1.15% spending decrease, while the top eight opposing precincts saw a 2.59% increase, indicating a $448,800 annual gap between the two groups.

Keywords: Menu Program, Aldermen, Infrastructure Maintenance, Local Politics, Spatial Distribution, Machine Politics

JEL codes: H41 H72 L98

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1 Introduction

Do local politicians use machine-style politics to drive public goods towards their supporters? Is spending bias exacerbated or curbed by local political competition? Because most municipalities allocate spending through collective decision-making bodies such as councils, it is usually difficult to attribute expenditures to individual politicians. However, one such program exists in the United States: Chicago's Aldermanic Menu Program. Through this program, the Chicago Department of Transportation (CDOT) gives each of Chicago's 50 aldermen a $1.5 million budget, an eponymous "menu" of common expenditures, and a map of 311 complaints in their ward. Using these resources, aldermen allocate funds to infrastructure maintenance, parks, and other public goods within their wards, even if they are not on the "menu."

This paper asks whether the menu funding towards each alderman's supporters or detractors changes after the alderman leaves office. If so, what determines the magnitude of this change? This paper uses a difference-in-differences design to compare the time trends of each supporting or opposing precinct before and after the alderman leaves office to answer this question. There are two cases where parallel trends are likely to hold: in close elections where the incumbent wins by a small margin and in cases where the incumbent is indicted and forced to leave office. In the former, both wards where the aldermen just barely won and just barely lost should have similar spending trends. Furthermore, both winning and losing aldermen in these cases should have similar expectations of winning, so they should behave similarly in the run-up to the election. In the latter, the timing of the in-office indictment is uncertain, which should preclude any anticipation.

This paper makes two contributions: first, it publicly introduces this setting's data, and second, it finds cases that support Dixit and Londregan (1996)'s theory of machine politics. Dixit and Londregan (1996) argue that the key to machine politics is for politicians to be more efficient at allocating public goods to their supporters than their opponents. Otherwise, it collapses to a competitive "Downsian" equilibrium. The paper finds some evidence for this bifurcation in the menu program setting using an annual panel of located spending data from 2005 to 2022. I find evidence that Bernie Stone, whom citizens long alleged to do this, allocated more spending to his supporters than his opponents. I find a large swing in fund allocation to the lowest and highest 20% of precincts by campaign contributions after Stone's 2011 loss to Debra Silverstein. The bottom 20% of precincts each saw $26,200 more in annual public goods, while the top 20% experienced a decline nearly double that. I look for a broader trend using two difference-in-differences approaches, one comparing wards where the incumbent barely won reelection to those where they narrowly lost, and another comparing indicted aldermen to other "entrenched" aldermen. I find no significant shift comparing incumbent aldermen who barely won and lost reelection. However, the indictment design shows a notable spending shift similar to the Stone case study. The shifts away from the top precincts are generally more robust than those towards the bottom precincts.

Section 2 describes the program's history, rules, and 2017 audit. Section 3 describes the public economics literature on public goods allocation and lobbying and the spatial and urban economics literature on infrastructure allocation and how this paper relates to both literatures. Section 4 describes how I developed the menu program spending panel, shows its summary statistics, and depicts an aggregate map of menu spending across Chicago for the past decade. Section 5 presents descriptive data for the case study of Alderman Bernie Stone, whom citizens alleged to favor supporters with menu program funds. Section 6 explains this paper's empirical strategy to determine if the Stone case study can be generalized to other aldermen. Section 7 shows the results of said empirical strategy, which finds that aldermen removed or retired due to criminal indictments, which has similar results to the Stone case study, albeit the results are not robust. Section 8 concludes.

2 Background

The aldermanic menu program was initiated in 1994 and continues today (Ferguson, 2017). The program delegates approximately $75 million every year to be split equally among the 50 aldermen in Chicago's city council to be spent on projects they unilaterally select for their ward, given a "menu" of acceptable expenditures. Each alderman allocates approximately $1.5 million per year to their ward. Chicago's Office of Budget and Management (OBM) tracks the program's spending, and the Department of Transportation (CDOT) manages it. Each ward is defined to be approximately equal by population every ten years, depending on the decennial census results. Still, the overall map is subject to a city council vote for approval. The Chicago Board of Elections draws the precinct map using the ward map, according to the available number of polling places, and each contains between 500 and 800 voters (Crowley, 2022). The 2012-2023 ward map (which has the majority of the data used in this paper) contains 2069 precincts for the 50 wards, averaging 41.38 precincts per ward (Crowley, 2022). Each year in the spring, the Mayor, CDOT, and OBM send letters to the aldermen explaining the program and providing a menu of cost estimates and a list of possible projects. Before the aldermen select projects, CDOT and OBM provide a briefing packet with 311 complaint data. Finally, aldermen spend the budget more or less as they see fit, with the only hard restriction being that they cannot spend more than their allotted annual budget. Because this program and elections occur in the spring, new aldermen can only spend their entire menu funds the following year and often rely on the previous alderman's programmed budget the year they are elected.

"Off-menu" expenditures are also allowed, of which most "off-menu" funds go towards Parks, Chicago Public Schools, and miscellaneous beautification projects such as trees, murals, decorative garbage cans, designer bike racks, and more (Ferguson, 2017). While on-menu items are typically also provided by other funding sources within Chicago's Capital Improvement Program, off-menu items such as murals and statues are usually directly credited to the aldermen, thus giving an incentive to reward supporters' loyalty with public goods. The program is unique insofar as it provides elected politicians a wide berth over a significant portion of the City's infrastructure budget and allows its use for items one does not typically think of as core infrastructure. An example of a portion of a menu from 2013 is shown below in Figure 1.

Figure 1: An Example of a menu from 2012/2013

DEPARTMENT/PROGRAM	2012	2013
CDOT	ESTIMATED PRICING	ESTIMATED PRICING
Residential Street Resurfacing	$36,000 for First 5 Blocks $58,000 for Subsequent Blocks	$38,000 for First 5 Blocks $66,500 for Subsequent Blocks
Residential Alley Resurfacing	$28,000 for First Alley $37,500 for Subsequent Alleys	$29,500 for First Alley $47,500 for Subsequent Alleys
Green Alley Program	$120,000 per Block	$150,000 per Block
Alley Speed Hump Program	$1,400 per Block	$1,400 per Block
Concrete Alley Aprons	$10,000 per Location	$10,000 per Location
Street Speed Hump Program	$3,700 per Block	$3,700 per Block

The Chicago Office of the Inspector General audited the program in 2017 and found that the program was rife with misallocation — because wards are defined to be approximately equal by population but not equal by infrastructure needs, so some dense wards get 80% or more of their needs met, while others get only 10% or less (Ferguson, 2017). Thus, the OIG found that the program resulted in significant funding disparities between wards relative to infrastructure needs. Secondly, the OIG audit found that from 2012 through 2015, the program permitted aldermen to use $ 15.1 million in menu funds for projects unrelated to so-called "core" infrastructure. Finally, after the 2012 redistricting, the OIG audit found that CDOT allowed aldermen to use $825,292 of menu funds on projects outside of where they were elected to represent so that they could spend it on their reelection wards.

3 Literature Review

Most literature on political allocation of public goods focuses on theoretical models to explain behavior but comparatively little empirical testing of that behavior. This literature looks primarily at the political incentives to redistribute. The early literature in political economy focused on variations targeting the median voter, the seminal paper being Downs (1957). This earlier literature was largely successful in explaining platform convergence in two-party systems. However, many political scientists and historians found this model lacking in describing cases of machine politics (Rakove, 1975; Golway, 2014). The harsh examples of the New York City Tammany Hall machine and the Chicago Democratic Machine are puzzling in a Downsian framework, as they maintained power through tight control of patronage jobs and distributing public goods to reward supporters. The resolution to this puzzle came in Dixit and Londregan (1996), which developed a general political model encompassing both patronage and targeting median voters. The model they use matches the Chicago setting to a tee: they assume that electorally motivated politicians have a fixed budget to allocate and can distribute it to a fixed number of pressure groups. In that model, they find two equilibria: one where politicians give to supporters and one to marginal voters, and the equilibrium depends on the incumbent party being more efficient at distributing to supporters.

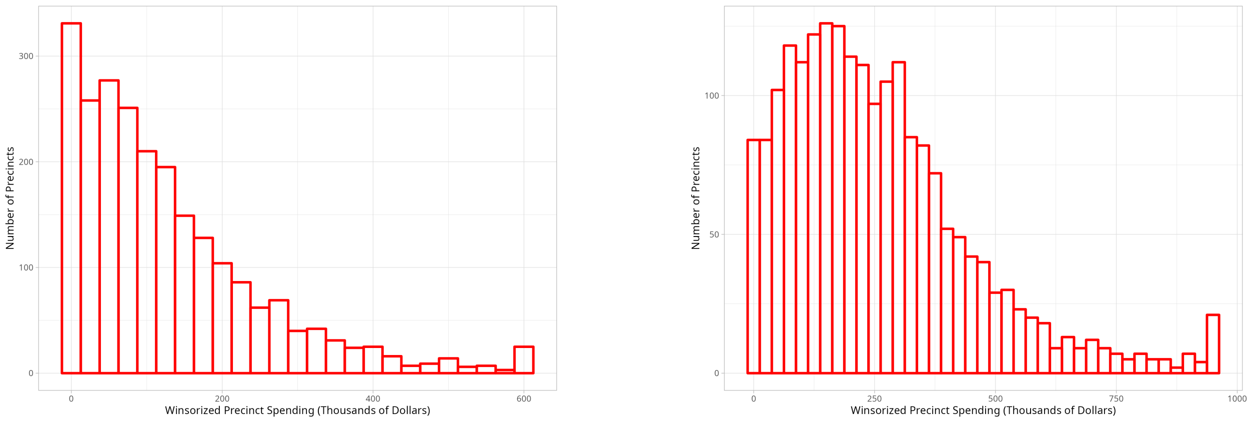
Since early contributions to the political economy literature (Grossman and Helpman, 1996), much work still focuses on identifying the effect of special interest groups on policy outcomes (Bombardini and Trebbi, 2020). This literature has taken different methodological approaches to quantifying this influence. One approach is to use structural models to simulate outcomes. This previous literature finds that influencing politics has high returns but that political influence has relatively small effects on policy outcomes on a national level and moderate effects at a local one (Kang, 2015; Finan and Mazzocco, 2021). Another approach is to take a more reduced-form approach and find some form of shock to identify how various outcomes change. For example, Margaret Frank, Hoopes and Lester (2022) find that governors in the US select place-based tax incentive locations more often when the tract's state representative is a member of the governor's party and is greatest with Republican governors. In another paper, Fowler, Garro and Spenkuch (2020) use an election regression discontinuity design and a first-differences design exploiting shifts in betting market beliefs and find that having a firm's supported candidate win has little influence on the firm's stock price in either framework.

This study is different from traditional political economy studies as it focuses on a municipal environment where the public good at play is primarily infrastructure. Thus, it is also related to the literature on municipal infrastructure provision and the new quantitative spatial economics literature. This literature includes Glaeser and Ponzetto (2018), Fajgelbaum et al. (2023), and Bordeu (2023). Glaeser's seminal paper focuses on infrastructure's "visible" and "invisible" costs. Overall, voters prefer overspending, as they see the benefits of infrastructure but not the costs. Local voters prefer under-building, as they see the externalities of the infrastructure. Glaeser uses this framework to explain why urban mega-projects declined in the US as urban voters became more organized. Fajgelbaum et al. (2023) examine how political economy influenced the planning of California's high-speed rail (CHSR) project. They find that preferences for widespread approval lead to the planner placing CHSR stations farther from dense metro areas than a politically blind planner. Finally, Bordeu (2023) looks at how infrastructure is allocated across a similarly decentralized city, Santiago, Chile, and finds that the sub-city municipalities over-invest in core areas and under-invest in areas near their boundary using a quantitative spatial model. She finds that infrastructure centralization would increase aggregate infrastructure investment and yield large welfare gains.

4 Data Description

This paper uses a panel of located menu expenditures containing the yearly allotted allocations from aldermen and their respective locations from 2005 to 2022. This dataset comes from annual menu spending reports publicly available from 2011 through 2022. OBM stores these reports in PDF format. They range from 150 to 500 pages long and contain information on each project's cost, description, and location. For example, the alderman reports a pair of intersections in a simple road resurfacing. In an alley resurfacing, the alderman often reports the four surrounding intersections. The location and description information is up to the alderman's discretion, and the quality of the information varies widely. I obtained data before then from records that were not previously publicly available through a FOIA request to the OBM (OBM, 2022). I scraped each of these reports and cleaned the resulting cost total, ward, and location description data. I then used the location description text to locate each project's described vertices using the Census geocoding API. If the Census's API failed, I automatically used Google Maps' API instead. In total, 43,596 projects needed to be located. I successfully located 83% of them. For example, spending on playground equipment would be a singular point, while spending on a street would be a line, and spending on all alleys within a given block would be a polygon. The spending for each project was then assigned to the precincts that overlapped with it by area overlapped. If a project were a \$10,000 quadrangle of $500m^2$, where 60% of the area was in precinct A, and 40% was in precinct B, I would assign \$6,000 to precinct A and \$4,000 to precinct B. I treated lines similarly, only using length instead of area. This dataset contains 41,381 precinct-year spending observations.

Figure 2 depicts two side-by-side histograms of the distribution of spending per precinct aggregated across the 2005-2011 period, which used the 2003-2011 ward boundaries and the 2012-2022 period with the 2012-2022 ward boundaries. The decentralized nature of the menu program leads to a considerable variation in spending per precinct, but the distribution has a long right tail. Both figures are winsorized at the 99th percentile to remove outliers.



(a) 2005-2011 (b) 2012-2022

Figure 2: Distribution of Spending per Precinct for both ward maps in the dataset

Next, Figure 3 depicts within-ward spending variation across Chicago using the 2012-2022 precinct map. The map shows that spending is often concentrated in a few precincts.

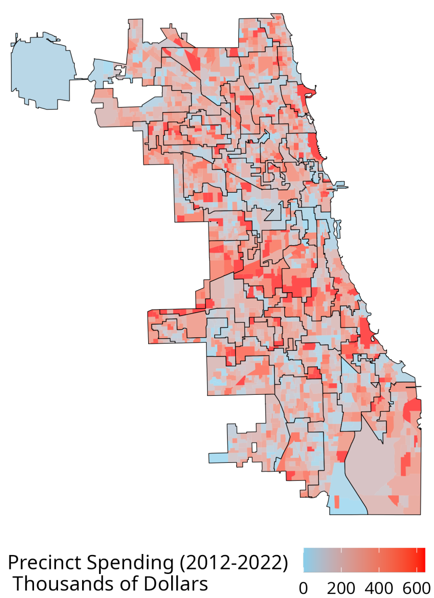


Figure 3: Map of Spending per Precinct, 2012-2022

To avoid issues with different levels of “observable” spending from year to year, I use the fraction of spending located in a precinct in a given year as the dependent variable for subsequent analyses. “Observed” in this context means one of the two methods above successfully located it to a location in Chicago. For example, if a precinct received \$50,000 in spending in 2019, but only \$900,000 of its ward's \$1.5M budget was located, then the fraction of spending located in that precinct in 2019 would be $\frac{50,000}{900,000} * 100 = 5.6\%$. I use this instead of dollar amounts because the amount of observable spending can shift from year to year, but that doesn't mean that alderman is prioritizing the precinct any less that year. Thus, if Y_{py} is the fraction of spending located in precinct p in year y, then $Y_{py} = \frac{S_{py}}{S_{wy}}$, where S_{py} is the spending in precinct p in year y, and S_{wy} is the total amount of ward w's successfully located spending in year y. Table 1 depicts summary statistics for this variable. Due to the long right tail of the distribution, the mean is much larger than the median. Half of the precincts get almost no spending each year.

Table 1: Summary statistics of fraction of total spending by precinct from 2012 to 2022

mean	median	sd	upper quartile	lower quartile
2.42	0.23	4.48	3.35	0

5 Bernie Stone Case Study

This section discusses the case of Bernie Stone, the exemplar of clientelistic behavior for this setting. Bernie Stone was an alderman in Chicago's 50th ward from 1973 to 2011. He was well known for his "political philosophy."

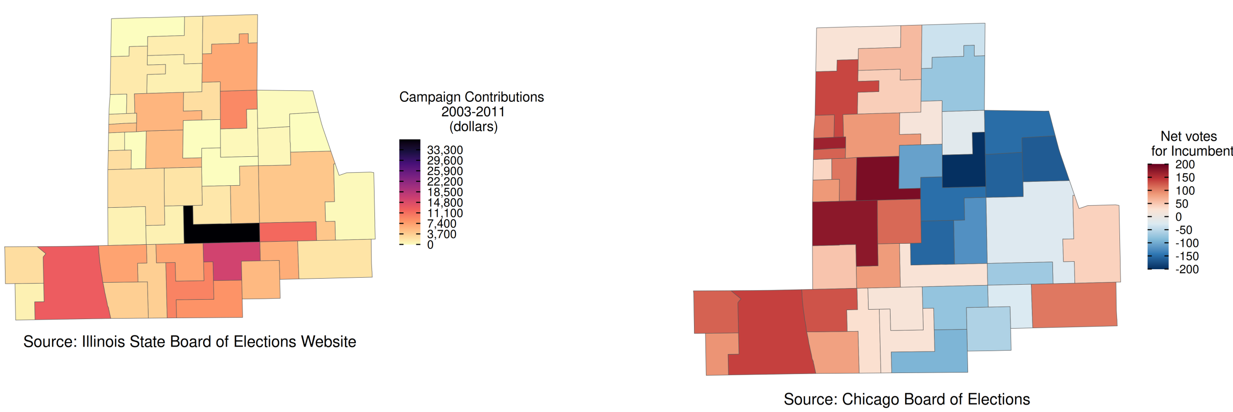
> "You take care of the people who take care of you — you know, the people who voted for you, That's not Chicago politics, that's Politics 101." - Alderman Bernie Stone (50th ward) (Zekman, 2009)

In fact an alderman who grew up in the 50th ward once remarked that,

> "Well, I grew up in the 50th Ward and you know, God bless [the late former Ald.] Bernie Stone, may he rest in peace, but I remember crossing California going west, every

street was resurfaced almost every year. They always had brand new lighting and then east of California, where he would lose the precincts consistently, I mean the streets were in shambles. Many people felt he was spending the bulk of the menu money west of California, where he was getting the bulk of the vote." - Alderman Carlos Ramirez-Rosa (35th Ward) (Vevea, 2017)

This quote is a clear example of the type of behavior that this paper seeks to investigate. This phenomenon could not be quantified previously because the CDOT did not make the 2005-2011 documents publicly available. Furthermore, the 2011-2022 data was in PDF form, making locating the spending tedious and difficult. This paper is the first to put numbers to this anecdotal evidence. Figure 4 depicts the precincts that supported Stone in the 2007 runoff election and the precincts that gave Stone the most individual contributions. Both maps show that the southwestern portion of the ward is the most supportive of Stone, on average. The two are also somewhat correlated, with a correlation coefficient of 0.14.



(a) Campaign contributions to Alderman Stone, 2003-2011

(b) Net votes for Alderman Stone, 2007

Figure 4: Alderman Stone's support in the 50th ward

Figure 5 gathers the top and bottom quintile of 44 precincts in the 50th ward by contributions to Stone and shows the average fraction of the total located menu budget spent in each quintile and the rest of the ward. After his reelection in 2007, Stone's spending per precinct was heavily concentrated in the precincts that supported him. After his defeat, spending per precinct became much more evenly distributed across the ward.

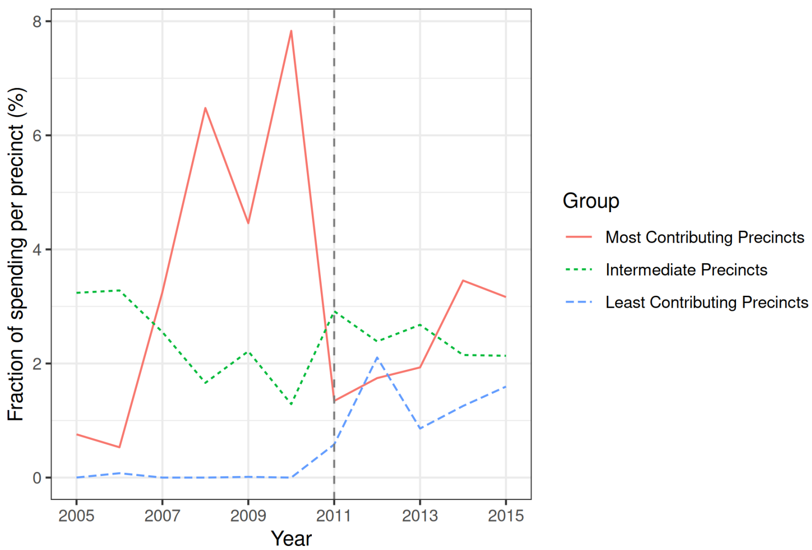
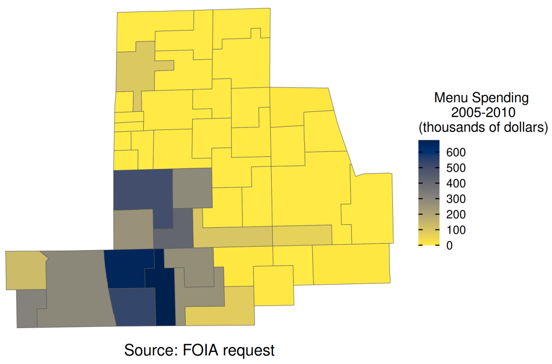
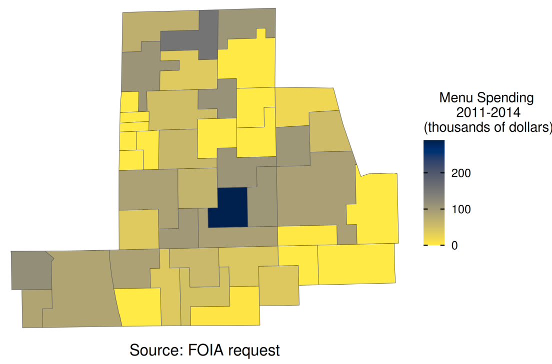


Figure 5: Average spending by precinct group in the 50th ward, 2005-2016

Figure 6 shows the shift geographically. It demonstrates a clear movement away from the southwestern portion of the ward to a roughly even distribution after Stone's defeat.



(a) 50th ward menu allocation, 2005-2010



(b) 50th ward menu allocation, 2011-2014

Figure 6: 50th ward menu maps before and after Stone's defeat

6 Empirical Framework

This section discusses the empirical framework used to analyze the data. I use the removal of an incumbent from office and the resulting breaking of the incumbent's patronage network to estimate the degree of patronage in the menu program. To do this, I use a difference-in-differences design to compare the spending trends of supporting or opposing precincts before and after the incumbent leaves office. The most standard specification of this design would normally be:

$$Y_{pt} = \beta T_{pt} + \alpha_p + \gamma_t + \epsilon_{pt} \tag{1}$$

Y_{pt} is the fraction of observed spending in precinct p in year t. T_{pt} is a dummy variable equal to 1 if the incumbent alderman was removed from office in year t. α_p and γ_t are precinct and year fixed effects respectively. ϵ_{pt} is the error term. β represents how much spending on an average precinct in the sample changes after an alderman is removed from office. Thus, in the case of estimating supporting precincts, a negative β would indicate that the incumbent alderman was allocating more spending to those that supported them than the following alderman would have chosen. Under parallel trends and homogenous treatment effects, this represents the causal impact of removing an alderman from office on spending in the precincts contained in the sample. Yet, this model should not be naively applied with two-way fixed effects due to the recent literature on heterogeneous treatment effects on two-way fixed effects estimators with staggered treatment timing (de Chaisemartin and D'Haultfœuille, 2020) (Callaway and Sant'Anna, 2021). There are a number of ways to address this issue, but I use the heterogeneous-treatment effect robust estimator proposed by (Callaway and Sant'Anna, 2021)[1].

This paper estimates four variations of equation 1. The first two rely on a close-election assumption to justify the parallel trends assumption. This assumption means incumbent aldermen who win by a small margin have similar spending trends to those who lose by a small margin. This study defines a close margin as 10% or less; this corresponds to approximately 1,200 votes. This assumption effectively means that incumbent aldermen who barely win allocate funds similarly to those who barely lose in the run-up to the election. I then examine two sets of precincts. The first set of precincts is the top quintile (8) precincts by vote margin for each ward in the 2015 or 2019 election, whichever is appropriate to the treatment group. The second set of precincts is the bottom quintile precincts by vote margin for each ward in the 2015 or 2019 election, whichever is appropriate to the treatment group. I use the years 2012 through 2022 to estimate this model due to the 2011 redistricting complicating the use of 2005-2011 data.

The third and fourth variations rely on a simultaneous set of indictments of aldermen in 2019,

[1] I do not use a continuous treatment design for reasons specified by Callaway, Goodman-Bacon and Sant'Anna (2021). To identify a casual response using a continuous treatment requires that low-dosage groups (ie, middling supporting precincts) would have the same response had they chosen a high level of support instead. This is in fact directly at odds with the Dixit and Londregan (1996) model's implication that for machine politics to exist, the politician must be able to distribute goods more efficiently to supporters than non-supporters. Therefore, using a continuous treatment design would be effectively assuming away the very phenomenon the design is estimating.

causing three aldermen to either be ineligible for reelection or to retire. These aldermen were Daniel Solis, Ricardo Munoz, and Willie Cochran. Daniel Solis left office after being caught for corruption by the FBI and wearing a wire to record Alderman Ed Burke, who was indicted in 2019 but not removed from office until 2023. Ricardo Munoz retired after reporters discovered he spent PAC money on personal expenses. Willie Cochran retired after pleading guilty to wire fraud and misusing campaign funds for gambling and personal expenses. I compare this group to a set of 10 control aldermen who were not indicted, have been in office for at least 10 years, and won reelection in 2019 in the general election, indicating they were not in a competitive election. To measure whether or not a precinct supported an alderman, I use the total number of campaign contributions donated to the aldermen from the precinct in the 2015 and 2019 elections. I do this because many "entrenched" aldermen have not faced a competitive election in decades, so net votes are not a good measure of support. Despite this, all aldermen still accept campaign contributions even when there is no challenger, so I use this to measure support. In this case, I expect the trends for the indicted and control aldermen will be the same, as they are all not in competitive elections, and thus, their spending preferences should be stable over time. Furthermore, the unexpected timing of indictments within the election would hopefully preclude any anticipatory behavior. In both cases, I cluster standard errors at the ward level.

7 Results

I compute the dynamic aggregation of the average treatment effect on the treated group for the least and most supporting precincts and display the results in Table 2. Also shown are the estimate's standard errors, confidence intervals, and Wald-test p-values for the pre-test of the parallel trends assumption. Both estimated ATTs are not statistically significant for the close election design. Furthermore, the least supporting precinct's ATT is not especially economically significant. Half a percent of the menu program's budget is roughly $7,500. That is not even enough to afford two speed humps.

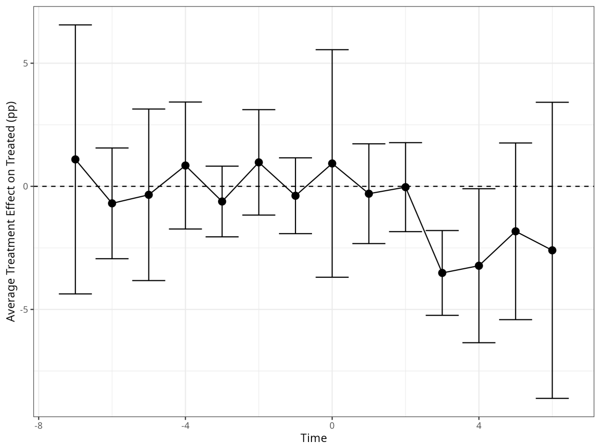
Additionally concerning are the extremely low p-values for the pre-trends test. This test indicates that the close election design likely does not guarantee that parallel trends hold. This failure may be because factors influencing the trend of infrastructure spending and needs correlate with the election outcome. Alternatively, it could be because the margin chosen is too large to ensure that the two groups are similar. The results of the competitive elections design are susceptible to the number of precincts included, often changing the sign of both estimated ATTs. Note that the treatment effect for the least supporting precincts is over five times larger than the treatment effect estimated in the competitive election design. Table 2 shows a much larger Wald-test p-value for the pre-trends test. These values indicate that perhaps the indictment design's assumption is more believable than the close election design's assumption. However, I also see that the most supporting precinct's treatment effect, while statistically significant, is similar in magnitude to the treatment effect of the competitive election design.

Table 2: Comparison of average treatment effects

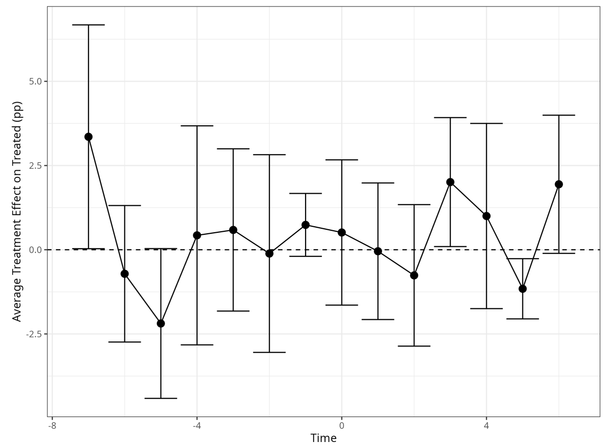
	Competitive Election		Indictment	
	Opposing ATT	Supporting ATT	Opposing ATT	Supporting ATT
ATT	0.50 (0.45)	-1.51 (1.12)	2.59 (0.78)	-1.15 (0.32)
95% Conf. Int.	(-0.38, 1.39)	(-3.71, 0.68)	(1.06, 4.11)	(-1.77, -0.52)
Pre-Trends P-value	0.005	0.076	0.199	0.174
Observations	1680	1680	1144	1144

Figure 7 depicts how the four designs estimated ATTs vary over time. All designs except for Panel 7d passed a placebo test for the last several years before the first treatment. Panel 7d shows evidence of anticipation in the year before the first treatment, as the 2019 estimate is significantly smaller than the other estimates. As inferred from the standard errors in Table 2, the estimated effect over time is noisy for all four designs. The large noise is likely because even a benevolent social planner will not allocate infrastructure spending using a highly auto-correlated spending rule. A road, once paved, does not need to be repaved for approximately 20 years, according to CDOT's life cycle analysis (Ferguson, 2017). There is a limit to how much spending can be preferentially allocated to a precinct before that alderman runs into harshly diminishing returns. Despite this, Panels 7c and 7d both show statistically significant effects post-treatment. The standard errors, while large, are much smaller for these panels, and the mean estimate is much more stable. This pattern also holds for the most supporting precincts, albeit in reverse. Thus, as the incumbent alderman leaves office, they allocate more spending to their most supporting precincts than their least supporting precincts. Therefore, the gap found must be taken with a grain of salt due to the high standard errors and the likely pre-trends violation.

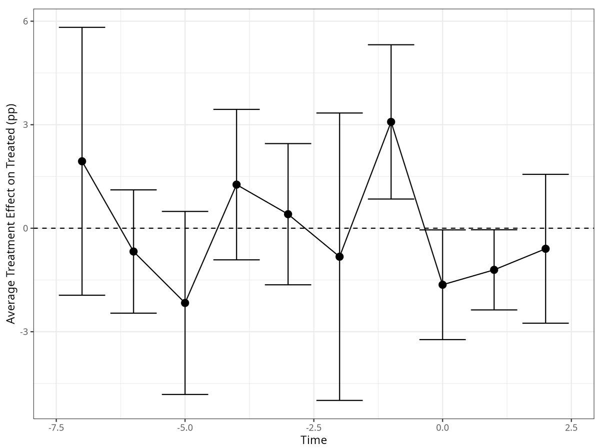
Figure 7: ATT over time for the four designs



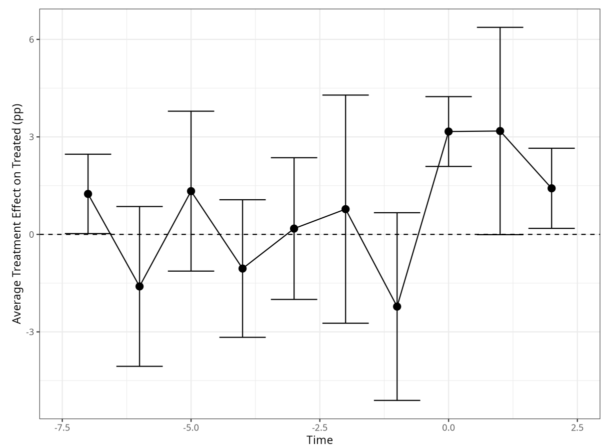
(a) Close Election: most supporting precincts



(b) Close Election: least supporting precincts



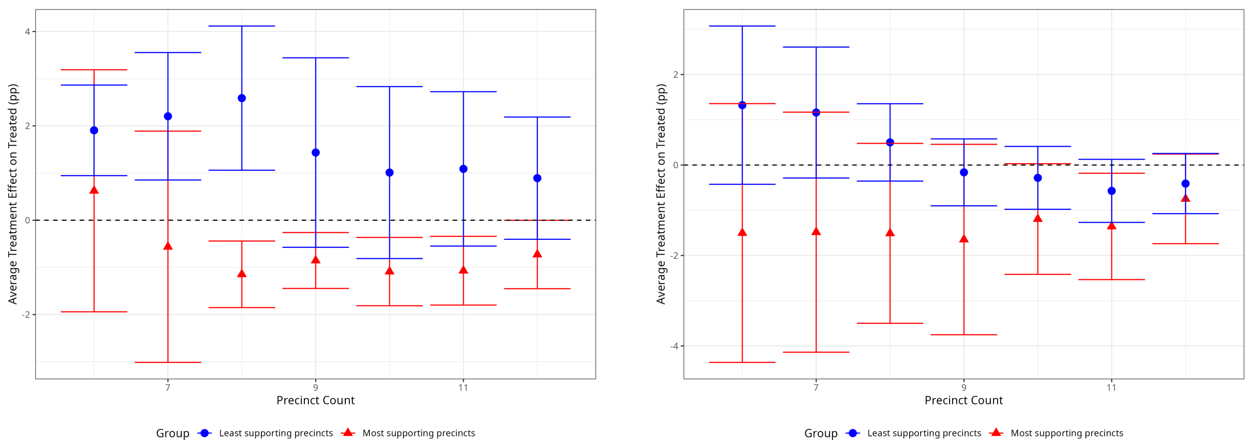
(c) Corruption: most supporting precincts



(d) Corruption: least supporting precincts

Lastly, the high standard errors beg the question of how stable the estimates are to the specification used. The specifications above use the top or bottom supporting quintile, which is eight precincts, as the 2012-2022 period has an average of 41.38 precincts. What happens when this number is varied? Figure 8 shows the estimated ATTs for different numbers of precincts. The answer is that the estimates for the least supporting precincts are relatively stable in magnitude but are only statistically significant for precincts 3-8. Most supporting precincts seem much more stable, as they are statistically significant for precincts 8-12.

Figure 8: ATT across number of precincts used



(a) Corruption

(b) Close Election

8 Conclusions

Overall, this paper finds some evidence that aldermen may sometimes disproportionately allocate spending to their most supporting precincts, particularly when they are long-entrenched and not facing a competitive election. The paper starts by verifying an allegation that a particular alderman disproportionately allocated spending to his most supporting precincts. Then, it uses two applications of a difference-in-differences research design to arrive at this fact. The first application focuses on aldermen who lost by a small margin and finds that the evidence for disproportionate spending is very weak. While the magnitude of the estimated effect for the top supported precincts in the close election design is large, it is not even close to statistically significant. However, The effect is economically large and statistically significant in the indictment design. The statistical significance is sensitive to parameters such as the number of supporting or opposing precincts per ward. Still, this design's economic significance stays the same regardless of the number of precincts included.

The results help build on the burgeoning urban economics of infrastructure literature by showing that political incentives can distort the allocation of infrastructure spending. Secondly, the differences between the competitive election and indictment designs show that electoral competition can be a powerful force in constraining the clientelistic tendencies of politicians. There is also a lesson in urban planners that while discretion can be useful, it can also be abused and lead to unintended consequences. Therefore, the capacity for discretion should be carefully considered when designing a program.

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