THE EMPIRICAL POLITICAL ECONOMY OF LOCAL ROAD MAINTENANCE OR DOES THE POLITICAL BUDGET CYCLE DRIVE DOWN LOCAL ROAD MAINTENANCE?

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Abstract

Political incentives affect infrastructure construction, but how incentives affect infrastructure upkeep, like road maintenance, is sparsely documented. Empirical results find different conclusions than theoretical evidence about road maintenance perceptions. Political alignment and local election cycles are leveraged using difference-in-differences to investigate if political incentives cause shifts in road maintenance. Robust results identify political distortions in invasive road maintenance timing. Local election cycles, which are widespread and frequent, shift road maintenance timing. Conservative calculations suggest local US elections

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cost at least \$185.5 million from 1960–2020, equivalent to 4 million meters of maintenance or maintaining all local Pittsburgh roads ≈ 1.45 times.[1] (**JEL Codes**: H40, H76, R42, R53)

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Roads and highways are linked to location of employment, population, and economic growth (A. Agrawal, Galasso, & Oettl, 2017; Baum-Snow, 2007; Chandra & Thompson, 2000; Duranton & Turner, 2011). Maintaining transportation links is crucial for economic activity, and U.S. states under-provide maintenance investment (Kalyvitis & Vella, 2015). However, maintenance is expensive; state and local investment in government nonresidential fixed assets like infrastructure cost $304.3 billion in 2018 (Zhao, Fonseca-Sarimento, & Tan, 2019).

According to Winston (2013), policymakers have wasted resources by investing, or not investing, in infrastructure projects not selected by careful analysis.[2] If political motivations shift timing and location of road maintenance projects at the local level (Glaeser & Shleifer, 2005), measuring the size and nature of shifts is crucial given the importance of infrastructure maintenance for economic activity (Kalaitzidakis & Kalyvitis, 2004; Rioja, 2003). In Figure 1, the month before the local mayoral election (October) has less projects during mayoral election years, which suggests political incentives are relevant for road maintenance in Pittsburgh.[3] The research question is if reduced fall maintenance, during mayoral election years, is due to political incentives.

A shift in maintenance across city wards and months due to election year incentives likely represents a deviation from the optimal maintenance plan.[4] Deviating from the optimal maintenance plan is costly, since longer delays in maintenance work leads to higher costs of maintenance (Burningham & Stankevich, 2005). Furthermore, new road construction is often more politically favorable in the long-run compared to road maintenance (Schmitt, 2015). Balancing new construc-

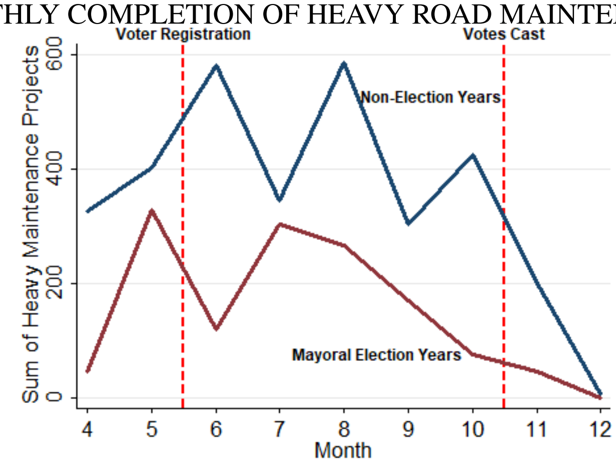
[2]Elected officials respond to incentives and one of their goals is to retain their position. Re-election is determined by receiving votes from specific geographic units, which could lead to inefficient spending patterns (Weingast, Shepsle, & Johnsen, 1981).

[3]Pittsburgh, Pennsylvania data is used in this paper.

[4]Deviating from optimal maintenance due to election cycles implies $Road\ Needs\ Repair = f(\beta * Election\ Year = 1, Climate,\ Truck\ VMT,\ other)$, $\beta = 0$. The amount of road repair necessary is not a function of election cycles, absent political incentives.

FIGURE 1

MONTHLY COMPLETION OF HEAVY ROAD MAINTENANCE



Note: Graph displays sum of heavy paving projects per year in the city of Pittsburgh from 2009-2017. The red line represents years when there is a mayoral election. The blue line represents years that do not have a mayoral election. Mayoral elections are held in 2009, 2013, and 2017. Numbers represent raw project, not adjusted to yearly averages. Red-dashed lines mark the length of the inter-election period. Non-election years refers to non-mayoral election years, thus it includes 2012 and 2016 which are national election years.

tion and maintenance of existing infrastructure has been shown to increase aggregate output and reduce income inequality (Gibson & Rioja, 2017). The research question is whether there is an additional channel, besides new infrastructure being perceived as relatively more politically valuable, through which political incentives interfere with road maintenance.

Existing results find seemingly contradictory signs for the political value of road maintenance/construction. Empirical results suggest road maintenance increases party vote share in a county-level analysis for one state (Huet-Vaughn, 2019), but the theoretical results suggest urban voters oppose road construction (Glaeser & Ponzetto, 2018). Brueckner and Selod (2006) and Glaeser and Ponzetto (2018) both consider the traffic and disruption of urban interstate construction a disamenity to local residents.[5] One discrepancy between theoretical (Brueckner & Selod, 2006; Glaeser & Ponzetto, 2018) and empirical analyses (Huet-Vaughn, 2019) is the geographic

[5]The empirical results in Huet-Vaughn (2019) suggest vote-maximizing politicians should strategically locate maintenance in places that are less likely to vote for them in an upcoming election, as that election approaches. The theoretical findings (Brueckner & Selod, 2006; Glaeser & Ponzetto, 2018) suggest vote-maximizing politicians should do the opposite.

level of interest. Different levels of analysis could be the sole reason the findings differ, but prior empirical work only takes place at a scale larger than the local city level. Previous attempts to estimate the effect of political incentives on urban infrastructure have occurred at the regional (Knight, 2005) or national (Rioja, 2003) level, despite the fact that government agents in the theoretical models (Brueckner & Selod, 2006; Glaeser & Ponzetto, 2018; Glaeser & Shleifer, 2005) are best thought of as being local leaders exercising power at the local level. More empirical work towards discovering the source of these discrepancies is warranted.

This paper uncovers the causal effect of political incentives on road maintenance decisions at the local city level using difference-in-differences (DD). The post period is mayoral election years. Treatment and control groups are defined using registered voters of the opposite party of the mayor. Proportion of registered voters of the opposite party is a plausible measurement of the intensity of political incentive to complete maintenance at certain times in city wards. The data are well-suited to address spatial scale as being a factor in seemingly contrasting prior findings.[6]

Road maintenance projects are shifted across months during mayoral election cycles according to alignment deviation of the constituency. During mayoral election years, wards with relatively large deviations in political alignment away from the mayor see a significant increase in road maintenance projects in summer months compared to more similar wards. This suggests road maintenance is perceived as a signal of competence to unaligned areas in the summer months of an election year. However, this pattern flips in October, the month before the votes are cast in mayoral election years. This is consistent with political leaders not wanting to upset constituencies with the

[6]The spatial scale of the current analysis is the local level; this allows investigation into whether spatial scale causes differences between previous empirical and theoretical findings.

disamenity of road maintenance as the election draws closer, suggesting road maintenance is both as a disamenity and signal of competence.

Using estimates from the literature on the cost of maintenance as a function of how long maintenance is delayed (Burningham & Stankevich, 2005), the DD coefficients are used to quantify the infrastructure maintenance financial cost due to local political incentives. These cost calculations are conservative due to the relatively uncontested political environment of Pittsburgh. The calculations suggest local elections in medium-large cities in the U.S. have cost over \$185.5 million in the past sixty years, over \$3 million a year.[7]

I LITERATURE

First, political economy and road maintenance is discussed. Then, the political alignment literature is described, since it influences the methods. Finally, research on road maintenance is summarized.

Theoretical Political Economy and Infrastructure

Political economy matters for infrastructure investment and maintenance. Glaeser and Ponzetto (2018) highlight the rise of disamenities in urban areas associated with road construction and the response by political actors to these constituent-faced disamenities.[8] The disamenities of construction explicitly mentioned include noise, pollution, and eminent-domain concerns. Glaeser and Shleifer (2005) show theoretically and through three case study examples, some mayors shape the

[7] Cities with at least 100,000 people are considered at least medium-sized (World Population Review, 2020).

[8] The conclusions of the model in Glaeser and Ponzetto (2018) are supplemented using an analytic narrative of U.S. road infrastructure in the post World War II era. The narrative simplifies the era into three rough chapters of U.S. national investment in roads: a period of over-investment due to national subsidies, a period of under-investment as the disamenities of construction became clear, and then a period where large sums were spent to mitigate the disamenities.

electorate to benefit their re-election possibilities. The so-called "Curley Effect," named for the infamous Boston mayor's extraordinary proclivity to pursue politically-minded transfers, shows local, elected officials reallocate public funds when political gains can be accrued.

Political Alignment

Many studies investigate the effect of political alignment on transfers resulting from federalist systems of government, where nationally collected taxes are distributed to lower levels of government. Solé-Ollé and Sorribas-Navarro (2008) study Spain's 900 municipalities over 10 years and finds intergovernmental transfers are more likely among levels of government that are of the same party. Similar investigations use data from India (Asher & Novosad, 2017), Brazil (Brollo & Nannicini, 2012), Portugal (Migueis, 2013), and Italy (Bracco, Lockwood, Porcelli, & Redoano, 2015). Bracco et al. (2015) develops a theoretical model which assumes rational voters who interpret public good provision as a signal of incumbent competence. This assumption stands in contrast to the disamenity assumption of Glaeser and Ponzetto (2018). Bracco et al. (2015) also assume the electorate does not observe the grant allocation; however, road maintenance is a visually salient public good (Glaeser & Ponzetto, 2018).

Road Maintenance, Public Capital Expenditure, and Growth

Road maintenance, in general, has been linked to economic growth. Rioja (2003) finds evidence of substitution to road maintenance from new "prestige projects" could increase GDP in a sample of Latin American countries. The theory is extended by Kalaitzidakis and Kalyvitis (2004) to allow the government to allocate towards maintenance and new public capital. Other extensions of the theory between maintenance and growth include: allowing maintenance to increase durability and quality of infrastructure (Agénor, 2009) and heterogeneous agents (Gibson & Rioja, 2017). [9]

II DATA

First, political institutions of Pittsburgh are described to justify the data used. Second, data sources are detailed. Next, the formation of the sample is described, descriptive statistics shown, and initial t-tests for differences in means, which are the foundation of the DD method, interpreted.

Institutional Details

Several institutional details about the city of Pittsburgh are relevant. Pittsburgh is governed under a mayor-city council system; the mayor acts as the head of a nine person council. Under leadership of the mayor, the council decides the location and timing of road maintenance projects on city-owned roads. The council "...regulates revenues and expenditures, incurs debt, and approves the final operating and capital budgets for the city." [10] In this system, mayoral political incentives could affect road maintenance.

The mayor is the only executive official elected through a *city-wide* vote, meaning the mayor's constituents are located across the whole city.[11] The city council members are only elected by votes in their respective districts, meaning the council members' constituents are only located in the

[9] Empirical findings suggest that Canada spends too much on public capital and that the reduction in spending should come primarily from maintenance instead of new capital to be optimal for economic growth (Kalaitzidakis & Kalyvitis, 2005). However, evidence from U.S. states suggests that maintenance spillover effects are more productive than new capital expenditures spillover effects (Kalyvitis & Vella, 2015).

[10] Source: `https://pittsburghpa.gov/council/index.html`. The council includes a standing committee that handles all details associated with the city Public Works department. The Public Works department may initiate contracts to pursue road maintenance projects, but the projects' timing, location and budget need final approval by the council and mayor. See `https://pittsburghpa.gov/council/public-works` for more details.

[11] The City Controller is also a city-wide vote, but the City Controller is not involved in road maintenance planning. See `https://pittsburghpa.gov/controller/`.

members' districts. Using city council votes is not appropriate for studying city-wide maintenance decisions, while alignment during mayoral election years may affect city-wide maintenance.

Wards

The Pittsburgh ward shapefile is publicly available from the Western Pennsylvania Regional Data Center. Measures of voter registration are annually updated after the May primary elections.[12] Figure 2 displays how wards deviate from the within ward average proportion of registered Republicans in Pittsburgh across wards across all years in the sample. Wards in orange signify relatively unaligned wards in a given year, while navy wards represent wards that were relatively more politically aligned. Mayoral election years (2009, 2013, and 2017) are shown on the diagonal. Figure 2 demonstrates adequate within- and across-ward variation in political alignment over the sample.

Maintenance Projects

Pittsburgh differs from many other cities in that it publishes a detailed road paving schedule which includes the year a project started, the exact date it finished, and the type of maintenance job it was.[13] Only the most heavy/invasive maintenance projects are used, because they are most inconvenient. They are most disruptive in terms of noise and air pollution and need a longer time to complete, potentially adding travel time to trips along that route.[14] Table 1 details project types.

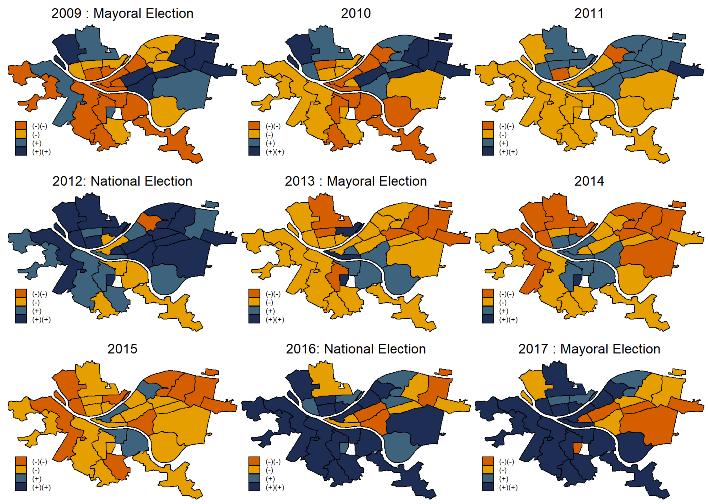
[12]Source: `https://www.alleghenycounty.us/elections/election-results.aspx`. This data is publicly available in every year of the sample from the Allegheny County Election Results website.

[13]The road maintenance data for the city of Pittsburgh, Pennsylvania is publicly available via the Western Pennsylvania Regional Data Center. There are N= 5,978 completed maintenance projects recorded in this data set for the period 2009-2017. Start date is not observed.

[14]Classification of "heavy" and "non-heavy" road maintenance based off of the authors' research and judgement.

FIGURE 2

WITHIN-WARD POLITICAL ALIGNMENT DEVIATION OVER TIME AND SPACE



Note: Within-ward political alignment deviations across Pittsburgh wards for all years of data (2009-2017). Mayoral election years are on the diagonal. Deviations in alignment within a ward are measured as 0.675 standard deviation changes from that same ward's median political alignment measure. The proportion of registered Democratic voters is used to proxy for political alignment. If a ward became "less politically aligned" (more registered Republicans) relative to its average alignment across the sample time period, it is shown in orange above as a negative change (-); "more politically aligned" (less registered Republicans) is shown in navy above as a positive change (+). Between 0 and 0.675 standard deviations from the median are shown in lighter shades of these respective colors (Small negative change: (-); small positive change: (+)) Greater than 0.675 standard deviations from the median in either direction are represented by darker shades of their respective colors (Large negative change: (-)(-); large positive change: (+)(+)).

TABLE 1

TYPES OF MAINTENANCE PROJECTS

Type of Maintenance	Description	Classification
Heavy		
Base Repair	Removing damaged pavement, determining cause of failure and appropriate solution, resurfacing of road	Heavy
SuperPave	Pavement mix designed to combat deformation and low temperature cracking	Heavy
Mill and Overlay (SuperPave)	Existing pavement removed, milled, surface overlaid with SuperPave pavement	Heavy
Mill and Overlay, $\geq$ 3"	Existing pavement surface removed, milled to a depth of greater than 3 inches, surface overlaid with new asphalt pavement	Heavy
Non-Heavy		
Mill and Overlay, $<$ 3"	Existing pavement surface is removed, milled to depth of less than 3 inches, surface is overlaid with new asphalt pavement	Non-Heavy
AC Overlay	Pavement is placed down on top of existing pavement, no milling of existing road	Non-Heavy
Mechanical Patching	Small areas and irregularities patched over	Non-Heavy
Profile Milling	Just the edges of the road are milled down	Non-Heavy

Note: Types of maintenance projects completed in Pittsburgh are shown above.

Sample

Road maintenance projects are joined to political wards using the boundaries they are geographically within. Each project has an associated date, enabling the creation of a ward-month-year level dataset. Next, yearly voter registration data are merged to maintenance projects. There are 32 wards over 9 years and 8 months, resulting in a sample of 2,592 observations.[15]

Descriptive Statistics

Table 2 shows descriptive statistics for the number of completed heavy maintenance projects by alignment and whether it is a mayoral election year. Wards are considered aligned if they deviate from their within-ward average towards being very aligned. Months are split into aligned and unaligned wards, because that is how the treatment/control groups are formed. The table is split by mayoral election year, because the method uses non-election years as years when difference in alignment has no justification for mattering for maintenance decisions.

The research design compares the difference between unaligned wards and aligned wards in non-mayoral election years to the difference in mayoral election years. Table 2 shows row-wise t-tests for differences in means, between mayoral and non-mayoral election years of the same treatment group and month. In aligned wards in June, 2.64 more projects are completed in non-election years compared to election years. However, for politically unaligned wards 2.84 fewer projects are done in non-election years in July. During election years, there is less maintenance in aligned wards in June and more maintenance projects in unaligned wards in July. In October, there are 2.55 more projects completed in unaligned districts in non-election years than election years.

[15] January-March observations are dropped, because there is little maintenance activity in these months. December 2017 is dropped, because the majority of these projects do not finish until after the sample period ends.

TABLE 2

DESCRIPTIVE STATISTICS, NUMBER OF HEAVY MAINTENANCE PROJECTS COMPLETED

	Mayoral Election Year				
	Non-Election Year		**Election Year**		**Row T-Test**
	Maintenance Mean	SE	Maintenance Mean	SE	Difference
Before Inter-Election Period					
April-Unaligned (n=144)	1.45	(0.54)	0.31	(0.19)	1.14
April-Aligned (n=144)	1.96	(0.52)	0.65	(0.29)	1.31*
May-Unaligned (n=144)	2.34	(0.58)	4.35	(1.21)	-2.01*
May-Aligned (n=144)	1.84	(0.47)	2.50	(0.77)	-0.66
Inter-Election Period					
June-Unaligned (n=144)	2.44	(0.80)	1.52	(0.90)	0.92
June-Aligned (n=144)	3.61	(0.80)	0.98	(0.31)	2.64**
July-Unaligned (n=144)	1.47	(0.42)	4.31	(1.01)	-2.84***
July-Aligned (n=144)	2.13	(0.44)	2.00	(0.74)	0.13
August-Unaligned (n=144)	3.41	(0.67)	3.77	(0.81)	-0.36
August-Aligned (n=144)	2.70	(0.67)	1.77	(0.52)	0.93
September-Unaligned (n=144)	0.67	(0.22)	0.98	(0.40)	-0.31
September-Aligned (n=144)	2.50	(0.45)	2.58	(0.87)	-0.08
October-Unaligned (n=144)	2.93	(0.73)	0.38	(0.19)	2.55**
October-Aligned (n=144)	1.50	(0.38)	1.21	(0.39)	0.29
After Inter-Election Period					
November-Unaligned (n=144)	1.29	(0.33)	0.56	(0.28)	0.73
November-Aligned (n=144)	0.79	(0.24)	0.38	(0.14)	0.42
December-Unaligned (n=120)	0.06	(0.05)	0.00	(0.00)	0.06
December-Aligned (n=136)	0.01	(0.01)	0.00	(0.00)	0.01

Note: The mean count of heavy maintenance projects per ward in each month-alignment classification is shown, separated by whether it is a mayoral election year (2009, 2013, 2017) or not. Descriptions of heavy projects are shown in Table 1. There are three election years and six non-election years in the data. The mean count of heavy maintenance over the total nine years is also shown. Alignment classification is determined by within-ward deviations in political alignment in a given year. N is the number of wards that fall into each month-alignment classification over the length of the data (2009-2017). SE = standard error. Row T-test conducted to compare election year completed road maintenance to non-election year completed road maintenance in each month. For the T-test column: *** p<0.01, ** p<0.05, * p<0.1.

III METHOD

The econometric model is difference-in-differences, in which June-October of mayoral election years is the treated period.[16] The model is specified

$$(1) \quad Maintenance_{myw} = exp(\beta_1 IEP_{my} + \beta_2 PA_{yw} + \beta_3 PA_{yw} * IEP_{my} + \boldsymbol{\mu}_w + \boldsymbol{\phi}_y + \boldsymbol{\gamma}_m),$$

[16]During mayoral election years, these are the months between the primary and the election date.

in which *m* stands for month, *y* for year, and *w* for ward. μ_w is a vector of ward fixed effects to control for unobservable, time-invariant ward-level heterogeneity. ϕ_y is a vector of year and γ_m is a vector of month fixed effects to control for variation in maintenance over time and seasonal, monthly maintenance. Maintenance stands for number of completed heavy maintenance projects. IEP stands for the inter-election period. Poisson estimation is appropriate, because the dependent variable is discrete.[17] To facilitate interpretation of the DD coefficient (β_3), OLS models are also used with the dependent variable being meters of completed heavy road maintenance.

Political Alignment

Ideally, treatment signifies a subset of wards where the mayor has different re-election incentives. Prior research defines treatment two ways: one, considering areas above a 50% threshold for a geographic area to be affiliated with a specific representatives' party. Two, comparing small differences near 50% (Lehne, Shapiro, & Eynde, 2018; Migueis, 2013). Leveraging a 50% threshold is impossible in this data, because 50% is outside the range of registered Republicans (2.5%-25%).[18]

To define a treatment indicator for an area where the mayor faces different re-election incentives, in the absence of a 50% threshold, within-ward deviation from ward averages are used. From the May primary elections files, the number of registered voters of each party is used to construct a measure of the political alignment. Political alignment is defined as $PA_{wy} = 1$ if:

$$PA_{wy} = 1(Z_{wy} - \overline{Z}_w > \tilde{Z}), \tag{2}$$

[17] Poisson models estimate unbiased, consistent coefficients if the conditional mean is correctly specified (Wooldridge, 1999). Poisson is preferred over negative binomial for two reasons. The first is that errors in the model are likely correlated by ward, so the preferred model estimates cluster-robust standard errors at the ward level. An implication of using cluster-robust standard errors in a Poisson model is that it has been shown to correct for over-dispersion of the dependent variable (Cameron & Trivedi, 2005). Another reason Poisson is preferred for panel data is negative binomial models have been shown to not be "true fixed-effects" models (Allison & Waterman, 2002).

[18] The distribution of proportion Republican in a ward-year is shown in Figure A.3b.

in which Z_{wy} stands for registered Republicans (in standard deviations from within ward average) in a ward in a year, $\overline{Z}_w$ is the mean political alignment in a ward over the entire sample, and $\tilde{Z}$ is the median deviation across all 288 (32 wards X 9 years) ward-year combinations.[19,20]

Pittsburgh's political environment is relatively uncompetitive. One may worry that even the within-ward deviation approach may not accurately capture the political behavior of the mayor given the lack of within- and across-party challengers during the sample period. We argue that if potential challengers within or across parties gain enough support, incumbency or re-election is no longer guaranteed. It is, therefore, in the controlling party's interests, even in the face of low levels of perceived competition, to make the greatest number of constituents happy. This prevents the rise in popularity of future political opponents.

Sensitivity to Choice of Political Alignment Cutoff. One issue is choosing $\tilde{Z}$ for PA_{wy} in Equation 2.[21] Figure 3 shows how meters maintained depends on within-ward, registered Republican Z-score to probe for sensitivity to choice of $\tilde{Z}$. Figure 3 suggests results are insensitive to choice of $\tilde{Z}$, an effect is found over the entire distribution of Z_{wy}. The relative slopes of the effects are consistent with the differences identified in Table 2.

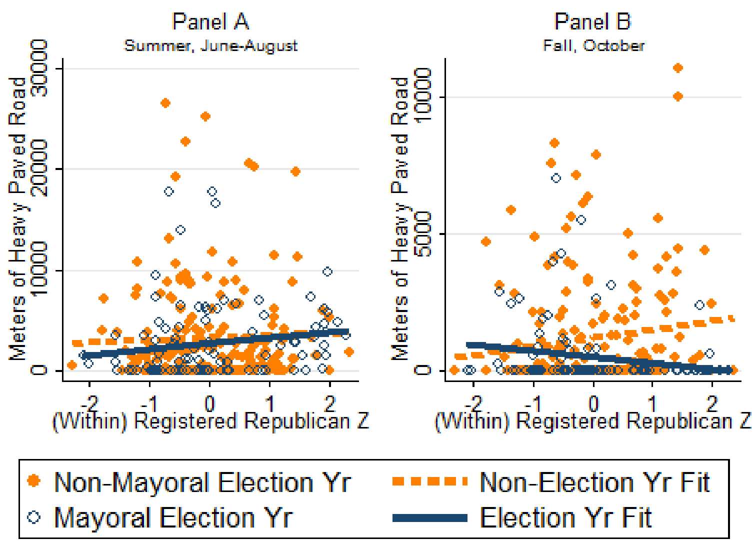
[19] The distribution of within-ward deviations are shown in Figure A.3a.

[20] This approach combines investigation of the head elected official (Glaeser & Shleifer, 2005) with the literature on federal grants and local governments based on political alignment (Bracco et al., 2015; Solé-Ollé & Sorribas-Navarro, 2008).

[21] Table 2 relied on choosing $Med(Z)_w$ over all years.

FIGURE 3

METERS OF MAINTENANCE BY WITHIN WARD REGISTERED REPUBLICAN Z-SCORE AND MONTHS IN INTER-ELECTION YEAR



Note: n = 288 ward-year observations (144 observations each for election and non-election years). Dependent variable is meters of road maintained. Independent variable is within-ward registered Republican deviations from within-ward average (Republican Z). Only heavy maintenance included. Legend consistent for all panels. Orange points represent meters of completed maintenance at each Z-score in non-mayoral election years, while blue points represent meters of completed maintenance at each Z-score in mayoral election years. The dashed-orange line is the line of best fit for non-election years and the solid blue line is the line of best fit for election years.

Increase in Unaligned Deviation Affects Maintenance Differently by Month. Panel A in Figure 3 suggests wards with higher proportions of registered Republicans receive more maintenance in summer of election years, and Panel B shows wards with more registered Republicans receive less maintenance in October of election years. This is caused by high Republican Z-scores having many non-zero values of meters of heavy maintenance in summer months of election years (Panel A, Figure 3), but many zero values of meters in October of election years (Panel B, Figure 3). The estimated effect of higher proportions of Republicans (slope of dotted, orange line) does not change paved meters of road completed by season in non-mayoral election years, consistent with a political incentives mechanism.

Identification

The model addresses seasonality of road maintenance in two ways. First, it compares politically aligned to politically unaligned wards in the same years and months when weather and other unobservables affecting maintenance are unlikely to be different across wards. Second, it controls for monthly differences using month fixed effects. This ensures results are not driven by seasonal maintenance patterns. Other covariates that are related to maintenance include the price of inputs and weather. It is highly unlikely that these unobservables are different across different wards, making them unlikely to bias β_3, the key variable of interest.

The identifying assumption is in the absence of the *mayoral* inter-election period altering political incentives, road maintenance in politically aligned and politically unaligned wards continues trending similarly during the months between the primary and general elections. Only two pre-registration months are observed in each of the three mayoral election years, so the common pre-trends are difficult to observe. An implication of the identifying assumption, which is more visually noticeable, is there are no discernible patterns or differences between aligned and unaligned wards in non-mayoral election years which begin during placebo periods of June-October.

Parallel Trends. Figure 4 presents maintenance over time, disaggregated by alignment, to investigate the implications of the identification assumption visually. Every year of data (2009-2017) is represented by a separate figure, because treated wards change every year as the within-ward political alignment deviation changes relative to the within-ward median. Mayoral election years

(2009, 2013, and 2017) are shown on the diagonal; red vertical lines define the inter-election period. Non-election years are shown in all other figures and use black vertical lines to define the months of interest. In each figure, navy represents politically aligned wards and orange represents unaligned wards. The figure also complies with the expectation that maintenance is seasonal: more maintenance takes place in the summer months.

In non-mayoral election years (off-diagonal figures), the number of completed maintenance projects is not systematically different for aligned compared to unaligned wards.[22] There is no systemic difference, aligned compared to unaligned wards, in October in non-mayoral election years. In election years (figures on the diagonal), there is a systematic difference between aligned and unaligned wards during the inter-election period. In June, July, and August of the three mayoral election years, unaligned wards have the same or more maintenance in 7 out of 9 months; in October, aligned wards have more or the same maintenance in all mayoral election year Octobers. Figure 4 is consistent with a corollary of the common trends assumption: there is no difference between aligned and unaligned wards in non-mayoral election years, giving some confidence to a causal interpretation of the results.

[22] In 2010 and 2011, the aligned and unaligned wards cross frequently. In 2012 and 2016, the unaligned wards are on a higher level. In 2014 and 2015, the aligned wards are on a higher level. In almost all of these off-mayoral election years, the month to month change looks to be either noise or the trend looks the same. This non-systematic difference/pattern in differences between aligned and unaligned wards in off-mayoral election cycle years supports the implication of the identifying assumption.

IV RESULTS

This section presents main results. First, difference in differences results are presented. Next, randomization inference shows statistical significance is not due to few overall or treated clusters.

Difference in Differences

Table 3 presents estimates from Equation 1. Panel A, column 1 considers the entire June-October period between voter registration and when votes are cast for the mayoral election; the DD coefficient is not statistically significant. A possible explanation is column 1 aggregates all months in the IEP together, and the opposite effects at the tail ends of the IEP cause the magnitude to appear relatively small and insignificant in the DD coefficient. Empirical studies have documented that time to election matters for how strong political incentives are (e.g. Berdejó and Yuchtman (2013)). Column 2 of Panel A only includes August-October in the IEP and finds no effect.

Column 3 only includes October in the IEP. The DD coefficient is positive and becomes statistically significant above 99 percent confidence in column 3. The DD coefficient can be interpreted that even though there is less maintenance during October, specifically October of the mayoral election years, there is comparatively more maintenance being completed in politically aligned wards.[23] The magnitude of the DD coefficient suggests there are 267 percent more projects in October of election season in politically aligned wards, compared to unaligned wards.[24]

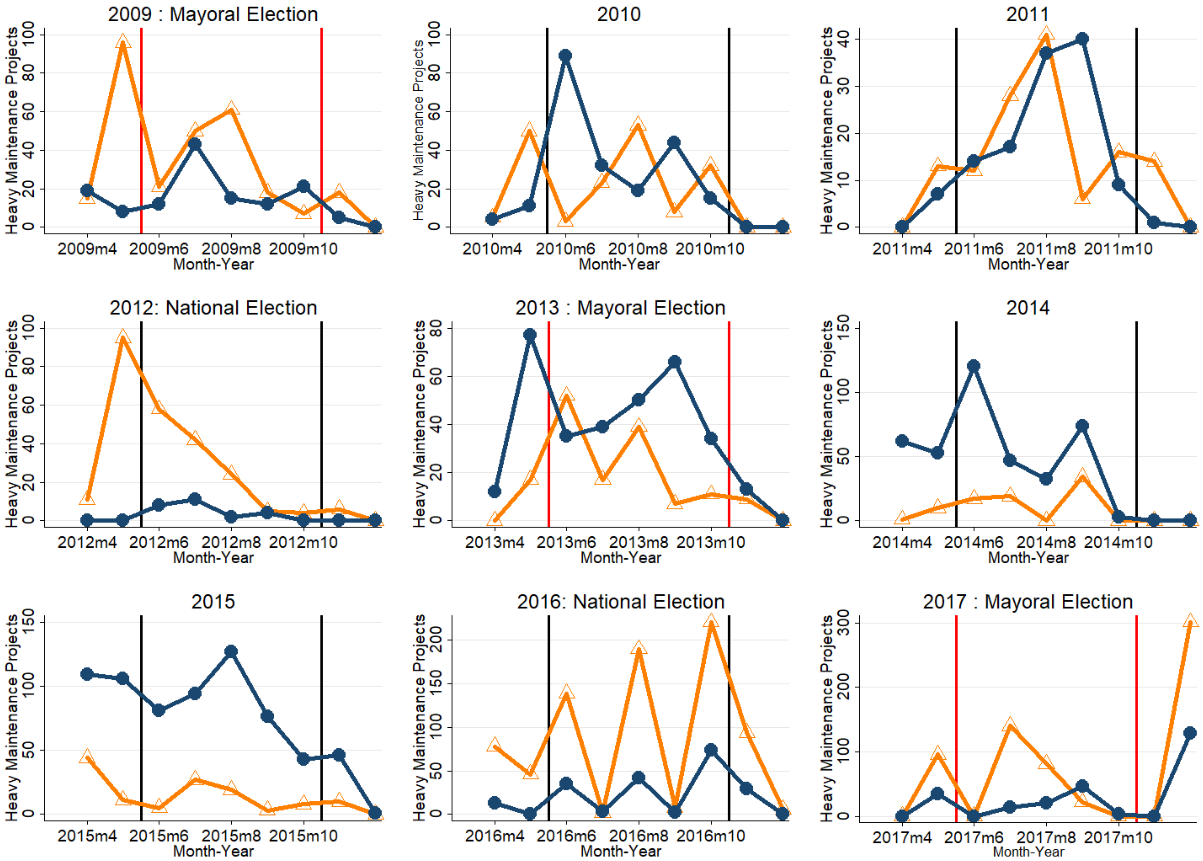
Panel B investigates months further from when votes are cast in November. In column 2, the effect of political alignment during election seasons is negative and statistically significant. Although there are more projects being completed in June-August, which is consistent with this

[23] Note that this holds the effect of October constant with month fixed effects also.

[24] The coefficient magnitude is calculated: $(e^{1.30} - 1) * 100 = 267$ percent.

FIGURE 4

MAINTENANCE PROJECTS BY POLITICAL ALIGNMENT AND YEAR



Note: Election years (2009, 2013, and 2017) for the mayor are shown on the diagonal using red vertical lines to define the inter-election period. Non-election years, representing the counterfactual inter-election periods in which the mayor is not up for election, are shown in all other figures and use black vertical lines to define the inter-election period. The navy series in each year represents the maintenance projects in wards that had a higher within-ward deviations towards being more politically aligned with the mayor (higher deviations towards less registered Republicans for a given ward-year). The orange series in each year represents the maintenance projects in wards that had higher within-ward deviations towards being politically unaligned. Dependent variable is count of heavy maintenance projects completed.

time being prime maintenance season and shown by the June-August in election year dummy, those maintenance projects are occurring in primarily unaligned areas. The magnitude of the DD coefficient can be interpreted as an 118 percent increase in politically unaligned places compared to politically aligned places in June-August of election seasons.

The results suggest there is a detectable effect of political incentives on road maintenance timing and location. Additionally, the signs are strongest and opposite in the tail months of the inter-election period. This finding is consistent with the political incentive argument: the election is most salient to voters the closer it is to the election. To avoid potentially upsetting or inconveniencing potential voters in the unaligned areas of the city close to the election, projects are strategically shifted. The relative magnitudes of the significant DD coefficients suggest there is a net reduction in the amount of maintenance completed in an election year since there are less projects substituted into aligned wards during October than are substituted out in June-August. It also suggests maintenance projects are both a disamenity and a signal of competence.

TABLE 3
HOW NARROWING MONTHS AFFECTS NUMBER OF HEAVY MAINTENANCE PROJECTS

Panel A: Removing Summer Months	(1) Jun-Oct	(2) Aug-Oct	(3) Oct
Political Alignment Above Deviation Median (PAUp)	-0.16	-0.24**	-0.24*
	(0.13)	(0.12)	(0.12)
Jun-Oct in Election Year (IEP)	0.03		
	(0.33)		
IEP X PAUp	-0.22		
	(0.20)		
Aug-Oct in Election Year (IEP)		-0.26	
		(0.21)	
IEP X PAUp		0.22	
		(0.25)	
Oct in Election Year (IEP)			-1.77***
			(0.57)
IEP X PAUp			1.30***
			(0.50)
Treated Observations	240	144	48
Panel B: Removing Months Near Election	Jun	Jun-Aug	Jun-Oct
Political Alignment Above Deviation Median (PAUp)	-0.20	-0.07	-0.16
	(0.12)	(0.12)	(0.13)
Jun in Election Year (IEP)	-0.68		
	(0.64)		
IEP X PAUp	-0.35		
	(0.62)		
Jun-Aug in Eletion Year (IEP)		0.46*	
		(0.26)	
IEP X PAUp		-0.78***	
		(0.21)	
Jun-Oct in Election Year (IEP)			0.03
			(0.33)
IEP X PAUp			-0.22
			(0.20)
Treated Observations	48	144	240
Observations	2560	2560	2560

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the ward level are shown in parentheses. Estimates are from Poisson conditional fixed effect model, shown in Equation 1. Ward, month, and year (uninteracted) fixed effects are included in every column. Grouping months by relative distance to the election are shown in columns 1-3. Panel A isolates the months closest to the election, while Panel B isolates the months furthest from the election. IEP stands for inter-election period. PAUp stands for political alignment. The DD coefficient of interest for every column in both panels is "IEPxPAUp." Treated observations denote the number of ward-month-year observations which are 1 for IEPXPAUp.

Inference Robust to Few Clusters

The confidence intervals in Table 3 are calculated using cluster-robust standard errors at the ward level. There are 32 wards and only some are treated in each mayoral election year, so the cluster-robust confidence intervals could be inappropriately narrow (Cameron & Miller, 2015). To address the potentially narrow standard errors, a permutation test is used which is less vulnerable to low amounts of clusters (Fisher, 1935).[25] This procedure is based on Fisher's exact p-value. The procedure randomly shuffles political competition Z-scores within wards across different years.[26]

Placebo distributions of test statistics are displayed in Figure 5. Figure 5a investigates inference on the DD coefficient for summer months. The actual test statistic from the DD coefficient, IEP X PAUp, in Table 3, Panel B, column 2, is less than 999 of the false test statistics. This implies an exact Fisher p-value of 1/1000 = 0.001. Figure 5b shows the distribution of Z-statistics for the same procedure, except now the coefficient of interest is IEP X PAUp from Column 3, Panel A, of Table 3. In this case, the actual Z-statistic on IEP X PAUp is greater than 992/1000 placebo Z-statistics, implying a Fisher exact p-value of 8/1000 = 0.008. Using an inference method less vulnerable to issues involving few clusters strengthens the conclusions of statistical significance.

V WARD BOUNDARIES AS VARIATION IN ALIGNMENT

Several concerns are addressed with spatial discontinuity plots.[27] The estimated DD coefficients could not be interpreted as causal if road maintenance causes changes in the political alignment of wards.[28] Although this is unlikely, the possibility cannot be ruled out in a DD framework. Additionally, if there are omitted third variables which are correlated with the treatment (political alignment) and outcome (road maintenance), then the DD coefficient is biased. Finally, leveraging

[25]This is a similar approach used by Cunningham and Shah (2018) to deal with narrow confidence intervals from few clusters.

[26]This keeps the distribution of political alignment within wards the same.

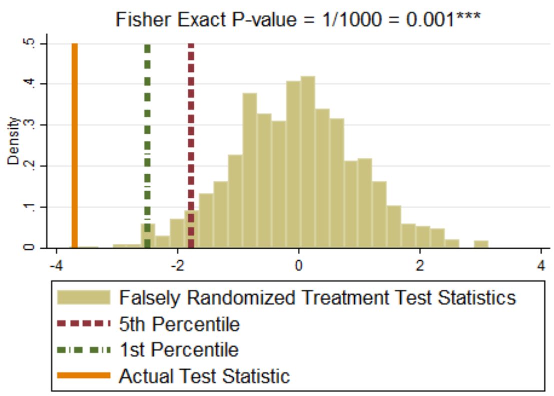
[27]D. R. Agrawal (2015) uses state borders to examine discontinuous differences in state retail taxes. Cantoni (2020) studies differences in voting costs (distance to polling location) for individuals that live near a voting precinct border. This study extends approaches that use spatial boundaries for geographic units to a new question.

[28]If the lack of road maintenance causes a certain ward to become less politically aligned, for instance, this would threaten the causal interpretation of the DD estimates.

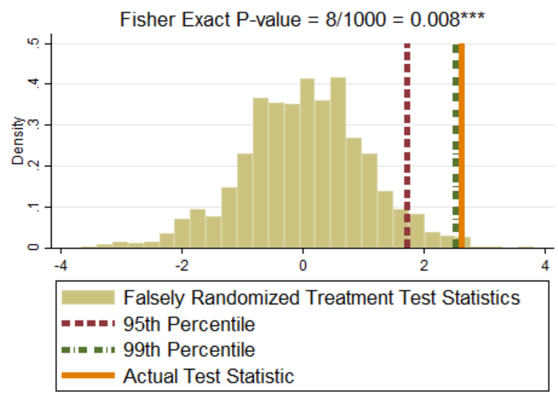
FIGURE 5

RANDOMIZATION INFERENCE

PANEL A: JUNE-AUGUST DD COEFFICIENT PLACEBO Z-STATISTICS DISTRIBUTION



PANEL B: OCTOBER DD COEFFICIENT PLACEBO Z-STATISTICS DISTRIBUTION



Note: Political alignment is shuffled within wards, across years. This leaves the distribution of alignment within-ward the same. Panel A: The test statistics displayed are from estimating IEP X PAUp in the Panel A, column 2 of Table 3 under falsely randomly assigned political alignment within ward across years. The actual test statistic is lower than the falsely randomized test statistics in 999/1000 permutations. In Panel B: The test statistics displayed are from estimating IEP X PAUp in Panel B, column 3 of Table 3 under falsely randomly assigned political alignment within ward across years. The actual test statistic is greater than the falsely randomized test statistics in 992/1000 permutations.

geographic variation helps address concerns about low variation in the treatment of proportion of registered Republicans in the DD coefficient of Equation 1. The plots compare road segments close to either side of ward borders where the political alignment is different between wards. leveraging geographic variation in how far the project is from being located in a certain ward.[29] Roads close to boundaries are probably similar; plausibly, the only difference is road segments on either side are treated by different levels of political alignment.[30]

Data Construction

The roads of Pittsburgh are split into 1-meter segments. The universe of roads in Pittsburgh is used to construct the road-segment level data set. The 2018 TIGER/Line shapefile of Allegheny County

[29]Wards boundaries are plausibly arbitrary and do not change in the sample.

[30]The unobservables that affect road maintenance such as labor costs, weather, auto traffic, etc. are likely similar on either side of the political boundary. This implies unobservables are unlikely to bias the effect of political alignment.

roads comes from the U.S. Census Bureau website. The 2018 file includes all roads in Allegheny County as of January 1, 2018, ensuring all roads that could have ever been maintained in the sample period are included. [31] A dummy variable is created for every 1-meter segment to indicate if that segment was maintained for every possible month-year combination in the sample.[32]

The distance from the midpoint of segments to nearest political ward boundary is calculated. Distances are converted to negative values if the political alignment deviation of the ward the project took place in was more negative than the political alignment deviation of the closest bordering ward.[33] Each boundary is assigned either an alignment switch or no alignment switch classification, for each year based on the political alignment deviation in wards on either side. [34]

[31] Interstates and state routes are excluded to limit the data to only roads the city of Pittsburgh is responsible for maintaining. The roads and projects are displayed in Figure A.2.

[32] There are approximately 210 million segment-month-year level observations.

[33] The possible closest ward boundaries are restricted to those interior in the city; boundaries defining the city limit or those bordering rivers on one side are dropped as possible closest boundaries.

[34] If a boundary is classified as unaligned, the two wards on either side of the boundary deviated in opposite directions in a given year. An aligned boundary had wards that deviated in the same direction of political alignment in that year. If a maintenance project is located in a ward with positive alignment, but was closest to an unaligned boundary, a positive distance value was assigned to that project; projects in relatively unaligned wards closest to unaligned boundaries were assigned negative distances. For example, if maintenance took place on a 1-meter segment in a ward that deviated towards political alignment that year and that project is closest to a boundary with an unaligned ward on the other side, the distance for that road segment in that year is defined as positive.1-meter segments that are located in wards with the largest deviation towards political alignment are assigned positive distances in cases where the two wards on either side of the ward boundary both deviated towards political alignment. 1-meter segments that are located in wards with the smallest deviation towards political unalignment are assigned positive distances in the cases where both wards on either side of a boundary deviated towards political unalignment.

Distribution of Roads at the Ward Boundary Cutoff

Figure A.5 shows there is a large increase in the number of 1-meter segments near the ward boundary border/cutoff. The large increase is consistent with roads also serving as ward boundaries. In the following analyses, road segments within ten meters of the border are dropped.[35]

Maintenance Differences at Ward/Alignment Boundaries

Figure 6 shows maintenance changes at ward boundaries for different combinations of months, in years with and without a mayoral election, and for differing alignment statuses on either side of the cutoff.[36] Due to sparse data, lowess fits are used to summarize mean maintenance instead of global fits, so differences at the cutoff are not influenced by distant outliers. Points right of the cutoff are in more politically aligned wards than wards to the left.

In Figure 6a, only summer months where alignment status changes at the cutoff in mayoral election years, are included. Figure 6a shows a reduction in mean heavy maintenance at the ward boundary cutoff for politically aligned wards. Both slopes are negative as the cutoff is approached from either side, but is steeper for aligned wards. In Figure 6b, there is no difference right at the cutoff. However, there is a difference that becomes apparent at 70 meters away from the cutoff.[37]

[35]This dropping is similar to donut RD approach. This approach is not what the donut approach is typically used for; it is mainly utilized for dealing with those observations most likely to have sorted into/out of treatment. An advantage of dropping projects is projects could extend over borders or be applied to boundary roads where it is difficult to differentiate between which alignment to assign to a ward. Road segments may also differ substantially due to their use as ward boundaries.

[36]Figure 6 shows mean probability of maintenance on either side of the ward boundary cutoff. Observations just to the right of the red line are road segments which are just inside a politically aligned ward. The y-variable has the interpretation of the probability that the segment is maintained, conditional on distance from being in a more politically aligned ward. The y-variable is a small number because there are thousands of road segments within each bin and maintenance is a relatively rare outcome.

[37]Whether roads 70 meters away from a cutoff are similar enough for unobservables to be similar on either side of the cutoff is debatable. It is believed this is a fair assumption.

In aligned wards, at 70 meters away from the cutoff in election years, there is an increase in road maintenance that does not happen also for unaligned wards.

Three falsification exercises are performed. The first examines non-mayoral election years, where the alignment status changes at the border, because there is no mechanism for maintenance to differ by alignment status outside of mayoral election years. Figures 6c and 6d show no difference in maintenance at the cutoff in non-election years. The next falsification exercises leverage wards where alignment does not change at the border.[38] In Figure 6e, there is a slight difference at the border, but the slopes are oppositely signed and so the difference is converging towards 0 at the cutoff. In Figure 6f, maintenance increases far from the borders on both sides of the cutoff.

Figure 6g uses wards where alignment status does not change at the boundary, in non-mayoral election years, finding no difference in maintenance at the cutoff. Figure 6h shows a difference in maintenance at the cutoff; however, the difference is due to the last point closest to the cutoff in aligned wards which is much lower than nearby points on the same side of the cutoff. The effects in Figures 6a and 6b are plausible and consistent with the DD results and a majority of falsification exercises are supportive of the mechanism of political incentives for differences at the border.

VI COSTS OF ELECTIONS FOR ROAD MAINTENANCE

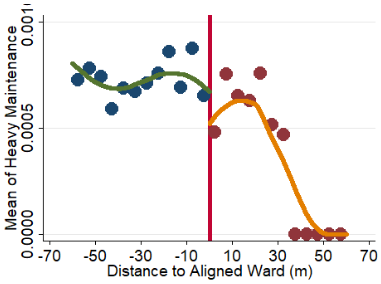
Table 4 replicates Table 3 using meters of completed maintenance as the new dependent variable, because it is easier to use for cost calculations. The DD coefficient in column 4 of Table 4 is interpreted as 605.76 meters less maintenance are completed in aligned wards during June-August

[38] Boundaries of wards that deviated in similar directions and intensities are included. For reference, ward boundaries that divide either two dark navy wards or two dark orange wards in Figure 2 are the boundaries classified as "alignment same."

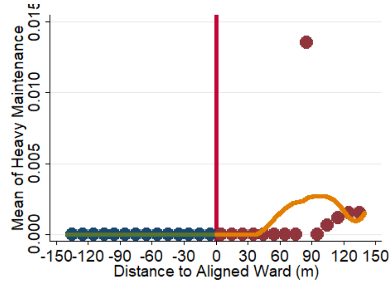
FIGURE 6

WARD-LEVEL SPATIAL RD PLOTS, COMBINING TESTS AND FALSIFICATION

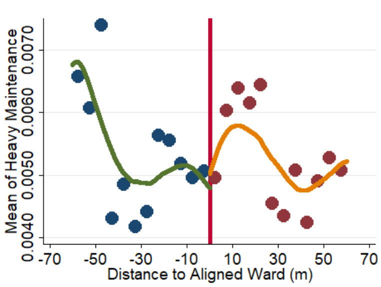
PANEL A: MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT CHANGE AT BORDER



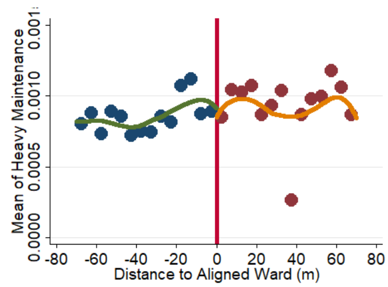
PANEL B: MAYORAL ELECTIONS, OCTOBER, ALIGNMENT CHANGE AT BORDER



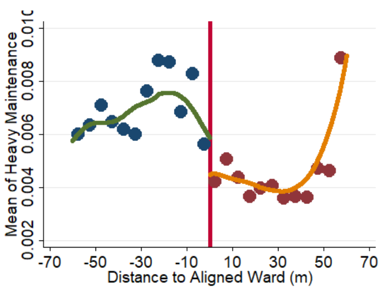
PANEL C: NON-MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT CHANGE AT BORDER



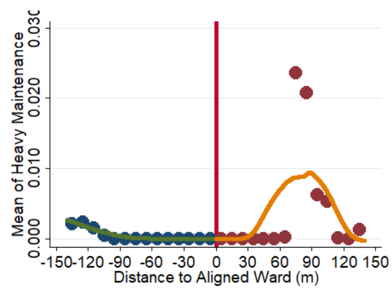
PANEL D: NON-MAYORAL ELECTIONS, OCTOBER, ALIGNMENT CHANGE AT BORDER



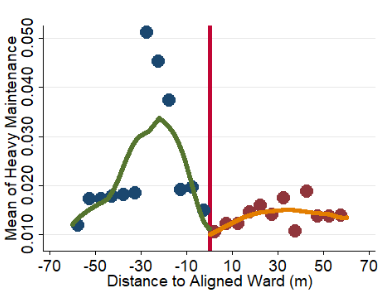
PANEL E: MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT SAME AT BORDER



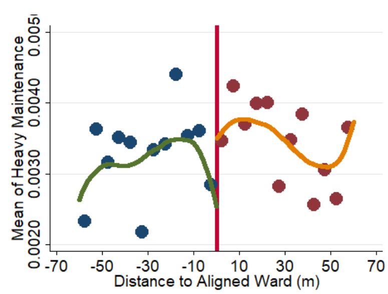
PANEL F: MAYORAL ELECTIONS, OCTOBER, ALIGNMENT SAME AT BORDER



PANEL G: NON-MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT SAME AT BORDER



PANEL H: NON-MAYORAL ELECTIONS, OCTOBER, ALIGNMENT SAME AT BORDER



Note: Panels D and H drop out national election years, 2012 and 2016. Blue dots are politically unaligned, red dots are politically aligned. X-axis is distance to more politically aligned ward (meters). Within 10 meters of boundary dropped due to the likelihood they are exactly on the border. Fitted lines are locally weighted sum of squares (lowess) using a tricube weighting function.

of election year. The DD coefficient in column 1 suggests that 565.48 meters of that maintenance is substituted into politically aligned wards in October of election year.

TABLE 4

CONTINUOUS METERS

	More Maintenance		Entire IEP	Less Maintenance	
	(1)	(2)	(3)	(4)	(5)
	Oct	Aug-Oct	Jun-Oct	Jun-Aug	Jun
IEP	-881.34***	-295.13**	-59.49	303.87	-535.91
	(218.48)	(137.40)	(202.73)	(228.20)	(446.76)
IEP * PA	565.48**	323.81	-69.37	-605.76***	-150.94
	(254.61)	(213.18)	(161.45)	(195.40)	(345.44)
Treated Observations	48	144	240	144	48
Observations	2560	2560	2560	2560	2560

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Estimates are from OLS two-way fixed effects models. Model includes ward, year, and month (uninteracted) fixed effects. Standard errors, clustered at the ward level, are shown in parentheses. DD coefficient of interest is "IEPxPA." The dependent variable is meters of road maintenance in a ward-month-year.

The estimates from Table 4, along with some supplemental data, are used to calculate the cost of political incentives for road maintenance in Pittsburgh.[39] Delayed road maintenance causes the cost of maintenance to be higher (Burningham & Stankevich, 2005). Taking the estimates from Burningham and Stankevich (2005), an exponential curve is fit to their two data points.[40] The equation of the fitted exponential curve is: (1.0153 * (exp(0.5796 * delayed years))). Plugging in 4/12 for "delayed years," this equation calculates delaying maintenance by four months causes maintenance to be 1.231 times more expensive.[41]

[39]These estimates only quantify the cost for road maintenance, but there could be other costs (Bauernschuster, Hener, & Rainer, 2017).

[40]Figure A.7 shows the fit. A (0,1) point is added, because no delay cannot make maintenance more expensive.

[41]The findings are 605.76 meters of road maintenance are delayed by 3-5 months from the June-August period until October. Splitting the 3-5 month difference, all road maintenance is assumed to be delayed by four months.

Using this multiplier requires knowing undelayed, per meter maintenance costs. The cost of 1 meter of road maintenance in Pittsburgh is $45.55 per meter on average.[42] The cost of the delayed meters multiplied by the cost multiplier extrapolated from Burningham and Stankevich (2005) (605.76 meters * $45.55 cost/meter * 1.231 delay multiplier) implies an additional cost of $33,966 due to political incentives per mayoral electoral cycle. Second, there are 605.76 meters less maintenance in politically aligned wards in June-August, but only 565.48 additional meters in politically aligned wards in October. This suggests 40.28 meters of heavy road maintenance are not completed in each mayoral election cycle. For reference, one small pothole is considered to be about 1 square meter, so one mayoral election cycle causes 40.28 small potholes in Pittsburgh.[43]

Assume the election cycle potholes are not repaired right away and are repaired at some point before the next election. For simplicity, the potholes assumed to be repaired in two years (splitting the difference between 0 and four years later). At 40.28 meters and a cost of $45.55/meter, the initial cost of this foregone maintenance is $1,835. Given a two-year delay multiplier of 3.236, the total cost of the roadwork that was not substituted from June-August in the same year is $5,938.[44] Adding together both the cost of the roads that are delayed during the season, $33,966, and the roads that are assumed to be maintained in at a later time, $5,938, is a total cost of *$39,904 due to one mayoral election cycle* in Pittsburgh.[45]

[42]For each year, the per meter average cost is calculated by taking the total paving expenditures in Figure A.1 and dividing by the total length of maintenance. Then, the average across years is calculated, weighted by the expenditure amount in each year. This is done to account for years that happened to have larger amounts of spending on paving. Not weighting like this does not change the average per meter cost by more than $1.92 per meter.

[43]Average pothole information found at: https://suma.org/img/uploads/documents/communitiesoftomorrow/Pothole%20Guidelines.pdf. Additional costs of potholes that are not included in the estimates are potential damages to vehicles attributable to potholes and potential time costs due to slower commutes caused by potholes.

[44]This is conservative, because the road maintenance could be put off much longer than two years.

[45]For reference, the per capita income for a Pittsburgh resident in 2017 was $51,187.

Across Comparable Cities

The previous section calculates costs for Pittsburgh; however, local election cycles are frequent and widespread, so estimates across the whole U.S. calculated. Comparable cities from the Federal Highway Administration's list of urban areas with more than 750,000 residents in 2018 are used.[46] One-election-cycle delayed maintenance costs Pittsburgh $39,904, so this figure is multiplied across forty-seven cities in the Federal Highway Administration (FHWA)'s list of urban areas. The cost of maintenance delays, across 47 cities, from one U.S. local election is $1,875,488.[47]

In addition to large cities, smaller-sized cities are also likely to suffer from mayoral election cycle distortions.There are 310 cities with a population of at least 100,000 (World Population Review, 2020).[48] Additionally, local election cycles take place frequently, so a time period over which to calculate costs must be chosen. There are three periods of road construction in recent U.S. history according to Glaeser and Ponzetto (2018); the second one begins in 1960.[49] Since 1960, sixty years ago, there have been fifteen local election cycles in thirty-seven comparable cities.[50] Multiplying the cost over cities with a 2020 population of at least 100,000, over the last sixty years, $185.5 million dollars has been lost due to delayed maintenance from local U.S. elections. An $185.5 million loss could maintain 4,072,446 meters at the Pittsburgh maintenance cost per meter, or the entire city of local roads in Pittsburgh (2.8 million 1-meter segments) 1.45 times.

[46] Source: `https://www.fhwa.dot.gov/ohim/onh00/onh2p11.htm`. Table A.1 shows these cities.

[47] To use more comparable cities, several variables from the FHWA data are used to exclude cities measurably dissimilar from Pittsburgh. Variables used include population, population density, total highway miles, highway miles per capita, highway miles travelled per capita, average annual daily traffic (AADT), etc. Because Pittsburgh sits near the average for these variables, cities not within two standard deviations of the average of each variable are dropped for not being comparable. Table A.1 also shows cities that were dropped and a description of the variable that caused ten cities to be dropped to build a more similar comparison group. Using these comparable thirty-seven cities instead, the total cost of one U.S. local election cycle for only similar, large cities is $1,476,448.

[48] According to World Population Review (2020), there are 19,495 incorporated cities, towns, and villages in the United States and 14,768 have populations under 5,000, making them very different than Pittsburgh.

[49] This period is characterized by increasing political organization and opposition to new construction, so it is used as the period over which local elections increase the cost of maintenance.

[50] Assuming a local election occurs every four years.

Low Political Competition Implies Estimates are Lower Bounds

Another factor leading costs being underestimated is if distortion due to political incentives is larger in other cities. This is a fair concern, especially given that Pittsburgh has not had a Republican mayor since 1934, and the nine person city council has been entirely Democratic since 1933. To understand how much potential there is for under-estimation of costs due to more political competition in other cities, compared to the Pittsburgh baseline, data on party of mayors are gathered going back to 1960.[51] Table A.1 lists the number of Republican mayors for each of the forty-seven cities from the FHWA list.[52] Of the forty-seven cities on this list, thirty-one have had at least one Republican mayor, implying they are more politically competitive than Pittsburgh.[53] This supports the claim the cost estimates are conservative when multiplied across other similar cities in the U.S.

Maintenance Shifts Have Consequences for Road Safety

Table A.2 shows suggestive evidence that local election cycle maintenance shifts are also related to car crash outcomes.[54] In ward-month-years with less maintenance, there are fewer crashes (Panel A, column 4), people involved in crashes (Panel B, column 4), and heavy truck accidents (Panel D, column 4). In ward-month-years with more maintenance, there are a greater number of major injuries (Panel C, column 1). These additional effects on safety are not included in any of the cost calculations presented in the previous section.

[51] Data were collected from city websites and publicly available information. Some cities have incomplete information regarding the political party of their mayor over time. Nevertheless, this constructed variable shows the variability of cities relative political "competitiveness" across the county.

[52] Number of Republican mayors is an appropriate approximation of political competition because the closer this number is to the midpoint of the number of local elections since 1960 (0,15), the more times the office has changed party control.

[53] The average number of Republican mayors is 2.33, suggesting that some other cities may be orders of magnitude more competitive than Pittsburgh.

[54] Car crash data comes from the Pennsylvania Department of Transportation (PennDOT) website: https://crashinfo.penndot.gov/PCIT/welcome.html.

VII CONCLUSION

This paper finds politically aligned wards have less maintenance projects in months farther from the election, but more maintenance projects in months close to the election. The results are not caused by maintenance seasonality, too few clusters, arbitrary definitions of political alignment or relying solely on temporal variation. Oppositely signed coefficients for months on either side of the inter-election period suggest road maintenance is both a disamenity and a signal of competence.

This paper makes three contributions. First, political budget cycle analysis is extended to a salient, observable public good. Evidence that political incentives interfere with road maintenance beyond reducing maintenance in favor of new projects is found. If maintenance is planned despite politicians favoring new construction, political incentives delay maintenance, leading to higher costs (Burningham & Stankevich, 2005). This is another way political incentives interfere with the optimal spending of public money, in the context of road maintenance.

The second contribution is advancing literature at the intersection of infrastructure and political incentives. This paper finds results consistent with both Glaeser and Ponzetto (2018) and Huet-Vaughn (2019), suggesting road maintenance can be both a signal of competence and a disamenity. Furthermore, some results are consistent with Huet-Vaughn (2019) at a smaller spatial scale, suggesting the interaction of maintenance and political incentives may not depend on scale.

Third, the results document a new source of political distortions to infrastructure maintenance: local election cycles. This new source of political distortion can be added to several already proposed by Winston (2013). The cost of this political distortion to infrastructure maintenance is calculated across cities with at least 100,000 residents (in 2020) and found to cost at least $185.5 million. These results and cost calculations provide a warning to policy-makers concerning road maintenance decisions; allowing politics to enter the maintenance decision-making process will harm the fiscal position of cities by increasing expenses at no benefit other than for political gain.

Some limitations which could be addressed with future research. First, other cities are not investigated, because historical maintenance data is not publicly available for other cities. The data includes only maintenance projects on existing roads, not construction of new roads. Construction is the main topic of interest in Glaeser and Ponzetto (2018), but maintenance is a close substitute. The maintenance data includes an end date but not an exact start date, so the exact amount of maintenance time for each project is unknown. Finally, the city of Pittsburgh is not politically competitive relative to other large cities. Low political competition suggests the findings could be lower bounds of the political incentive mechanism's effect on local road maintenance.

Detter and Fölster (2017) suggest a way to reduce the impact of political concerns is to have financial asset managers make decisions. This has the drawback of reducing accountability, but a potential benefit of reducing distortion due to political incentives. In Pittsburgh, one election costs less than the income per capita of a Pittsburgh resident, making effects ambiguous.[55]

[55] In a more politically competitive city with more distortions, this option warrants further consideration.

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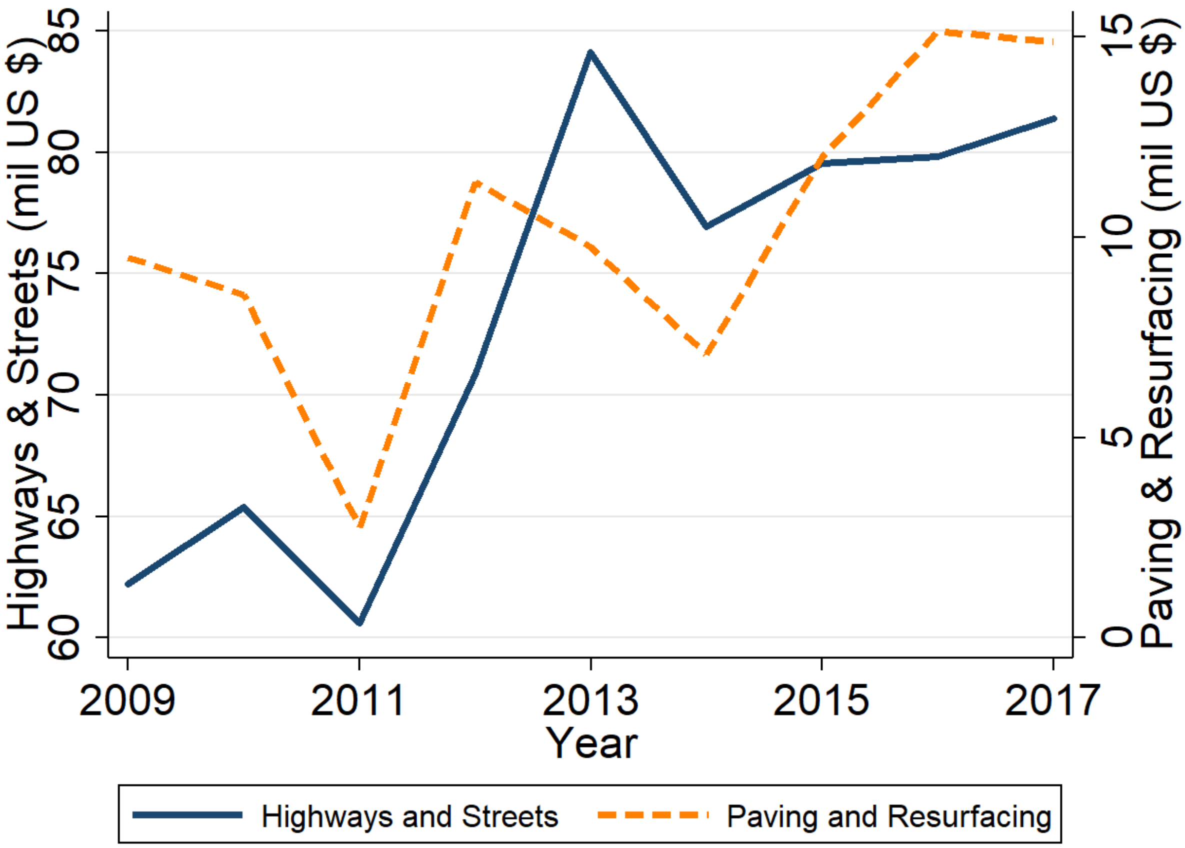
A ONLINE APPENDIX

FIGURE A.1

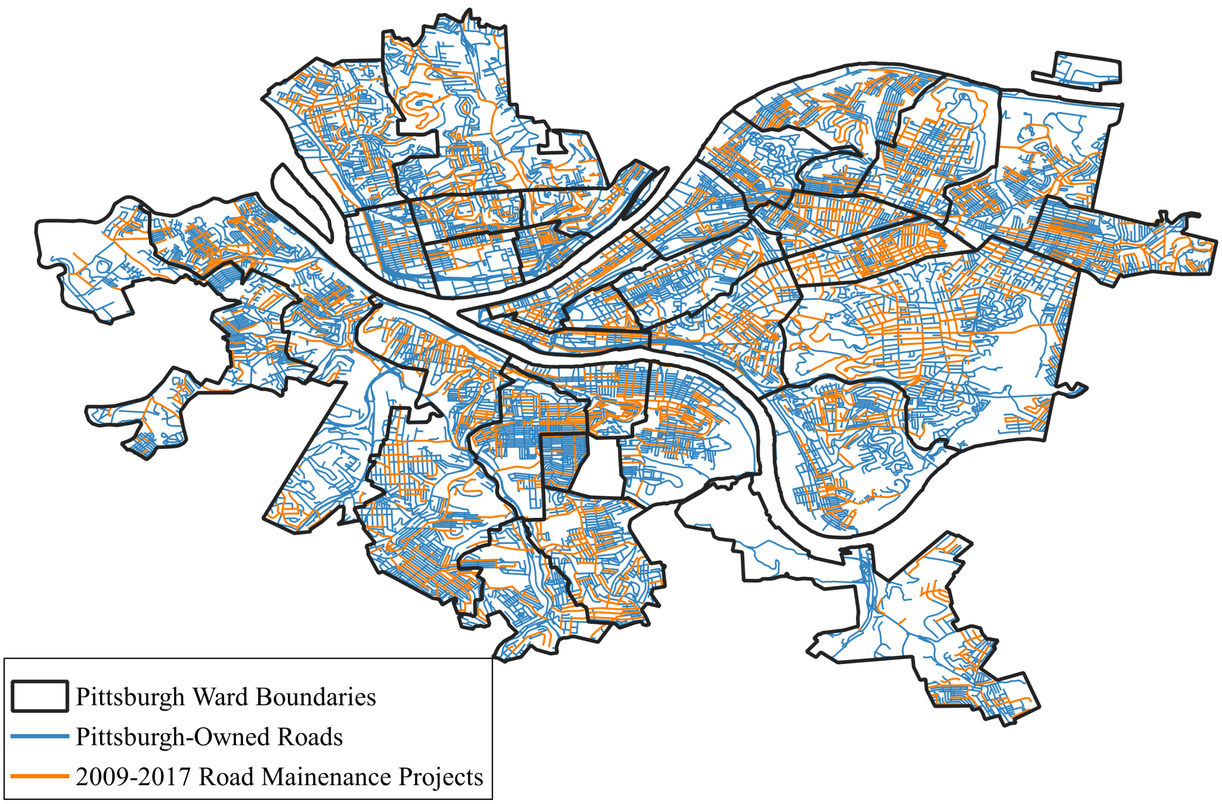
PITTSBURGH EXPENDITURES (2009-2017)



Note: Graph charts the expenditures on roads and road maintenance in the city of Pittsburgh for the length of the sample (2009-2017). The navy line represents total expenditures on highways and streets (construction, repair, etc.), while the orange-dashed line represents the expenditures just on paving and resurfacing. Sources: Pittsburgh Comprehensive Annual Financial Reports (https://pittsburghpa.gov/controller/cafr) and Pittsburgh Capital Budgets (https://pittsburghpa.gov/council/capital-budgets)

FIGURE A.2

MAINTENANCE PROJECTS AND ROADS SUPERIMPOSED ON POLITICAL WARDS

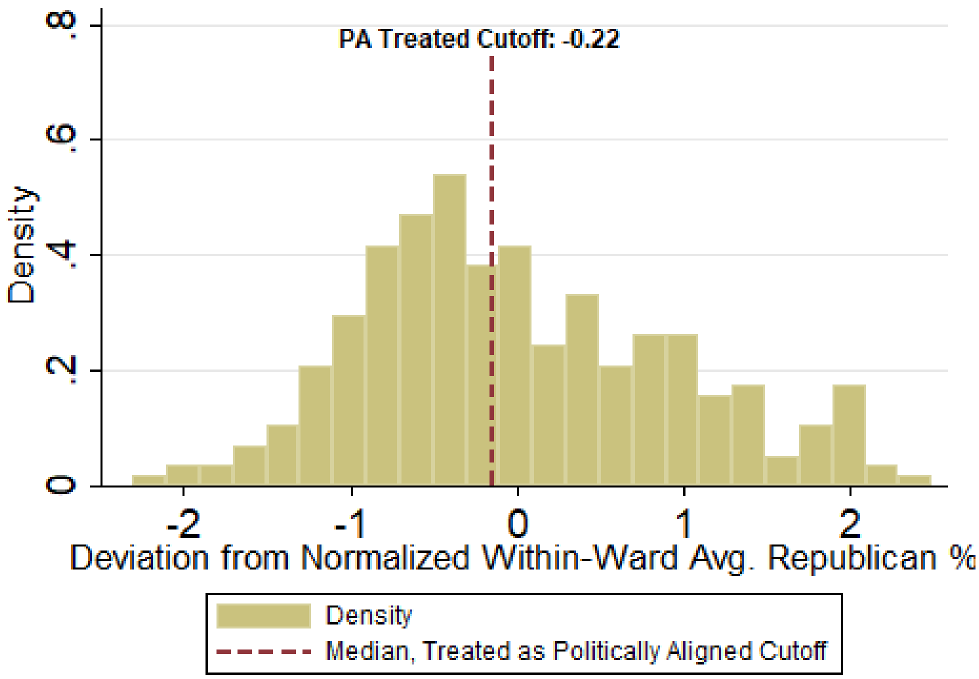


Note: This map of Pittsburgh shows the total universe of city-maintained roads and where maintenance occurred during the sample period. The blue lines are all city-maintained roads, and the orange lines show segments where maintenance occurred. Thick black lines denote ward boundaries.

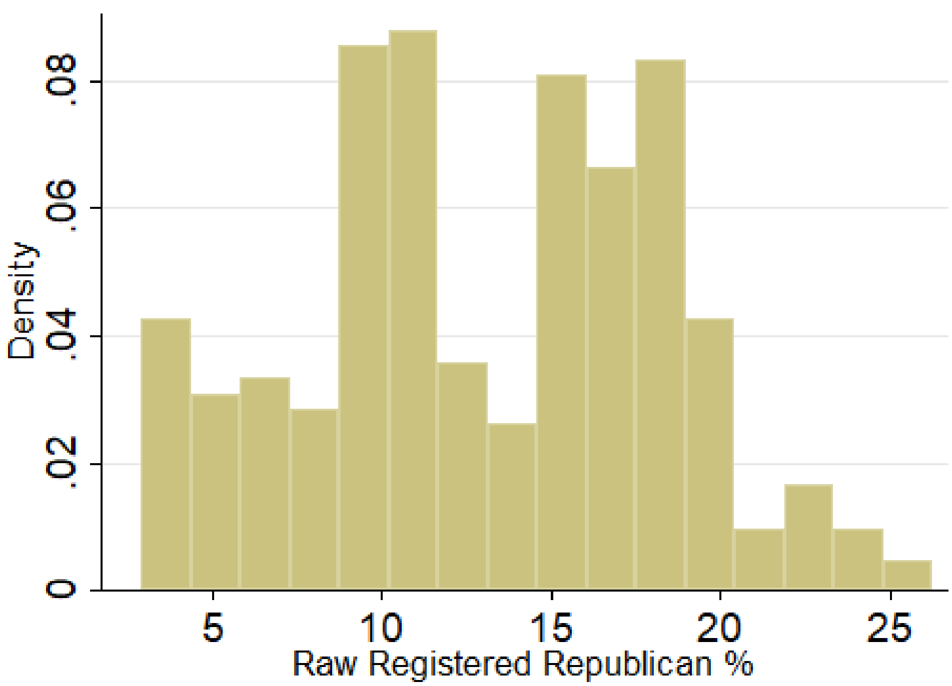
FIGURE A.3

DISTRIBUTIONS OF POLITICAL ALIGNMENT

PANEL A: WITHIN-WARD ALIGNMENT CUTOFF



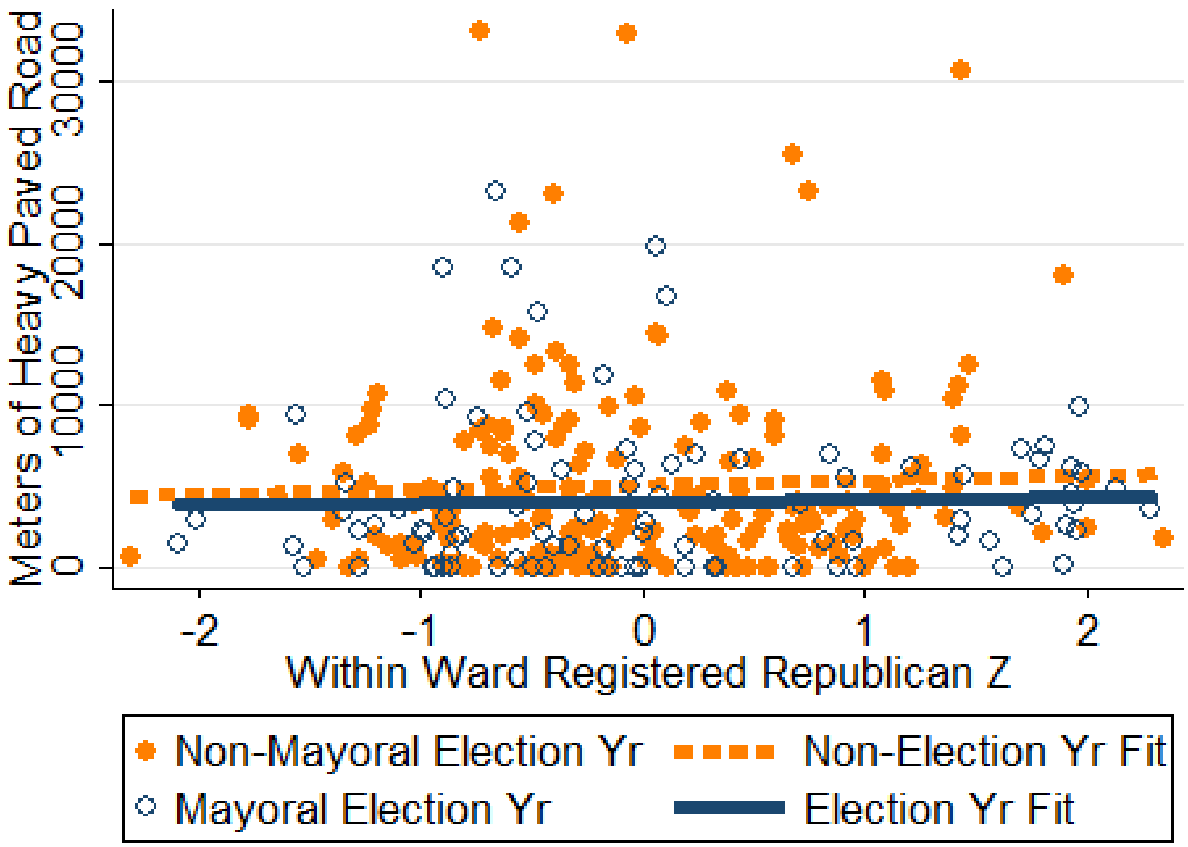
PANEL B: RAW REPUBLICAN PERCENTAGE PROPORTION



Note: N = 288 ward-year observations

FIGURE A.4

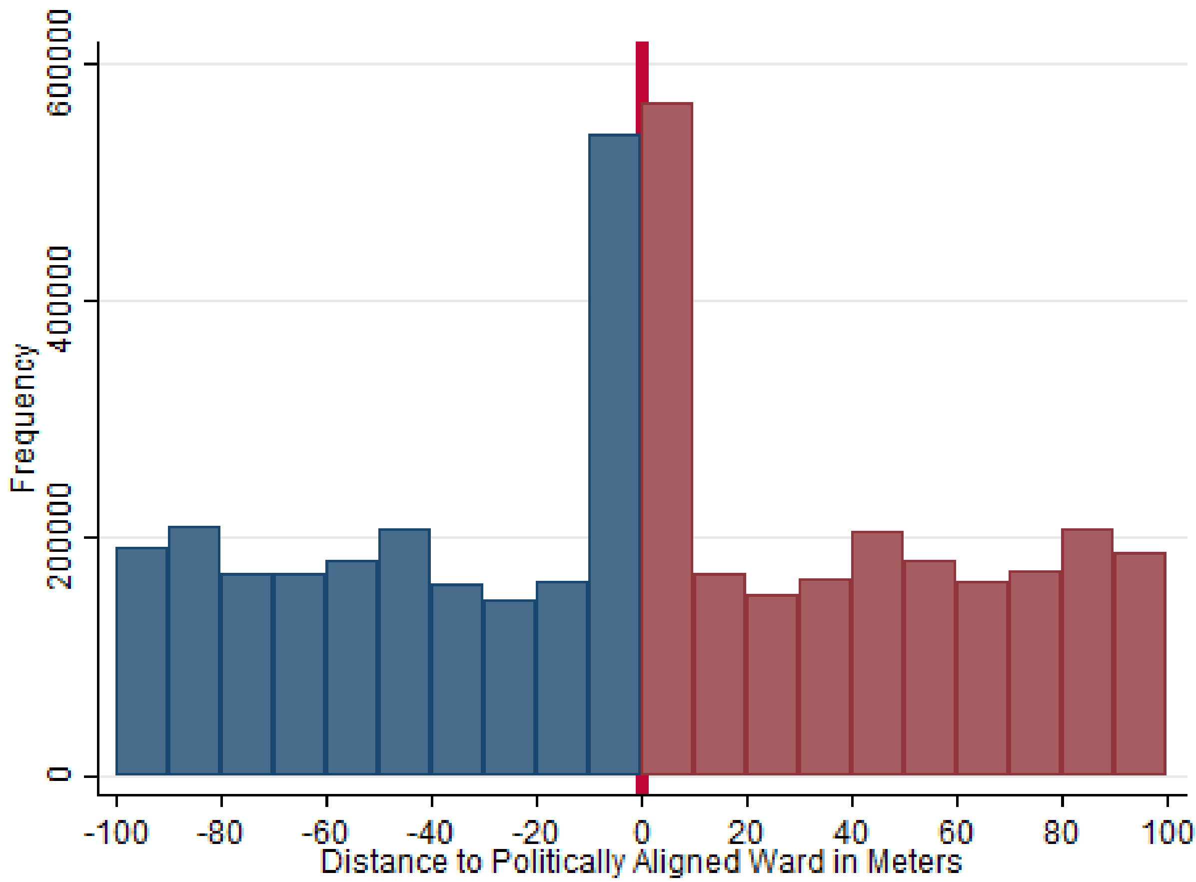
NUMBER OF 1 METER ROAD SEGMENTS BY DISTANCE TO WARD BOUNDARY



Note: 1 segment per year kept, because political alignment changes yearly.

FIGURE A.5

NUMBER OF 1 METER ROAD SEGMENTS BY DISTANCE TO WARD BOUNDARY

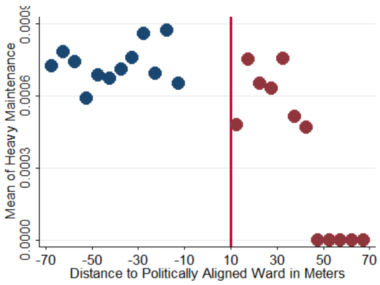


Note: 1 segment per year kept, because political alignment changes yearly.

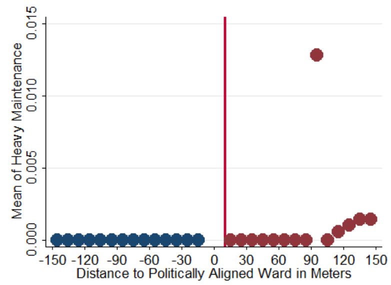
FIGURE A.6

WARD-LEVEL SPATIAL RD PLOTS, COMBINING TESTS AND FALSIFICATION

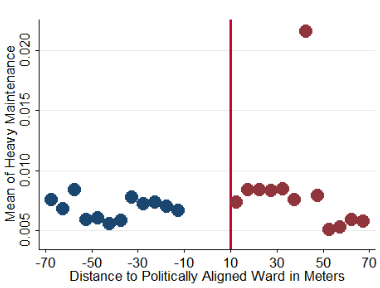
PANEL A: MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT CHANGE AT BORDER



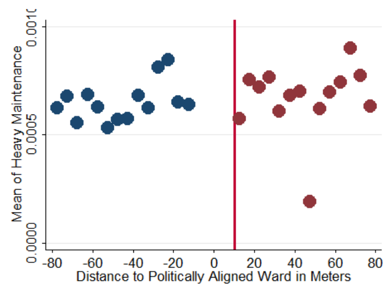
PANEL B: MAYORAL ELECTIONS, OCTOBER, ALIGNMENT CHANGE AT BORDER



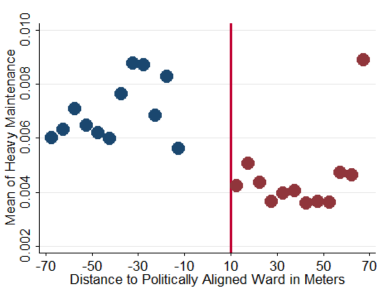
PANEL C: NON-MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT CHANGE AT BORDER



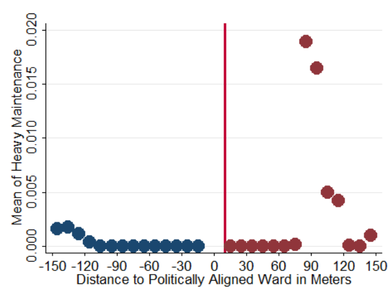
PANEL D: NON-MAYORAL ELECTIONS, OCTOBER, ALIGNMENT CHANGE AT BORDER



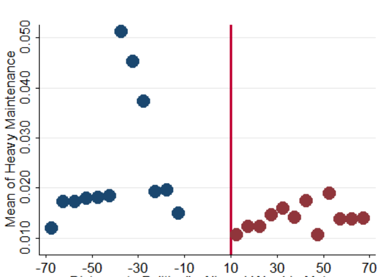
PANEL E: MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT SAME AT BORDER



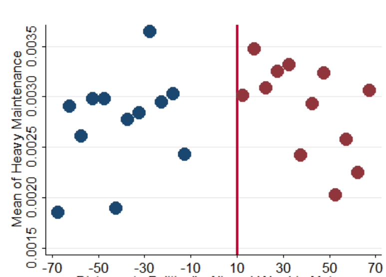
PANEL F: MAYORAL ELECTIONS, OCTOBER, ALIGNMENT SAME AT BORDER



PANEL G: NON-MAYORAL ELECTIONS, JUNE-AUGUST, ALIGNMENT SAME AT BORDER



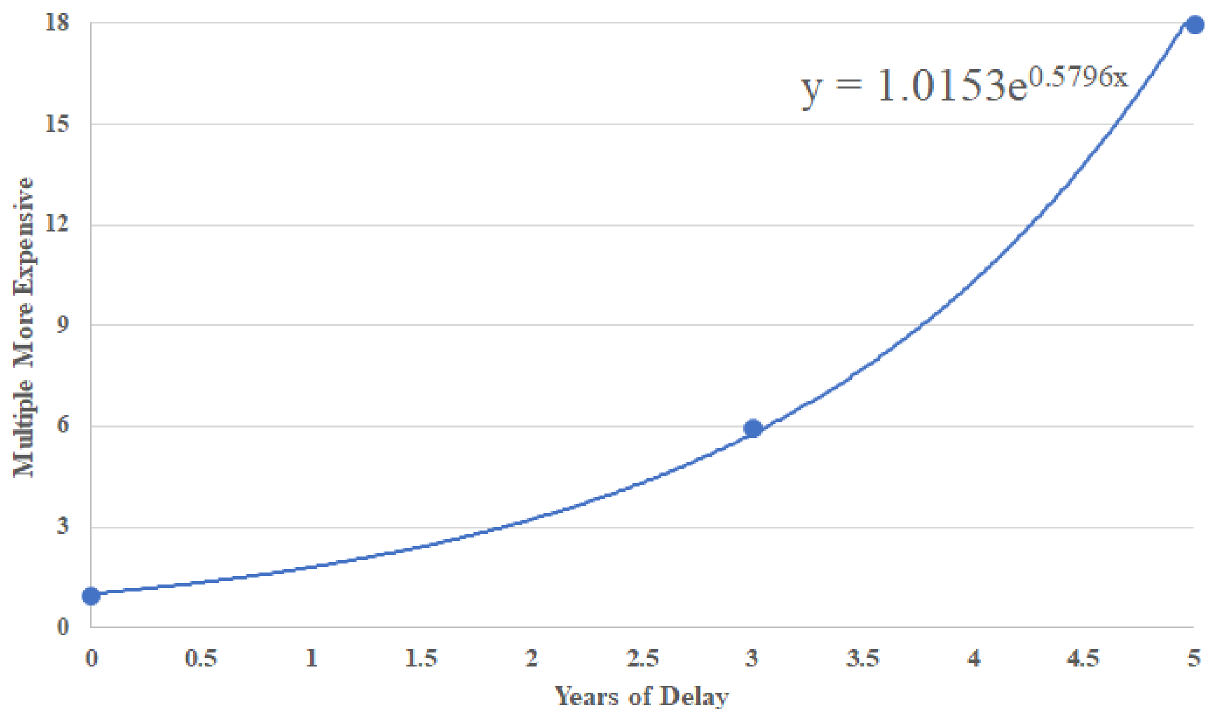
PANEL H: NON-MAYORAL ELECTIONS, OCTOBER, ALIGNMENT SAME AT BORDER



Note: Panels D and H drop out national election years, 2012 and 2016. Blue dots are politically unaligned, red dots are politically aligned. X-axis is distance to more politically aligned ward. Within 10 meters of boundary dropped due to the likelihood they are exactly on the border.

FIGURE A.7

THE COST OF ROAD MAINTENANCE DELAYS



Note: Exponential function extrapolated from two points which are noted in Burningham and Stankevich (2005). We added a point at (0,1), because it is likely there is no extra cost from no delay. This reduces the R-squared from 1 to 0.9995.

TABLE A.1

FEDERAL HIGHWAY ADMINISTRATION STATE & URBANIZED AREA STATISTICS: POPULATION OVER 750,000

Urban Area	Variable Outside of Two SD from Mean	Number of Republican Mayors Since 1960
New York Northeastern NJ, NY	Urbanized Population ↑	3
Los Angeles, CA	Urbanized Population ↑	2
Chicago - Northwestern IN, IL	Federal-Aid Urbanized Land Area ↑	0
Philadelphia, PA		0
San Francisco - Oakland, CA		1
Detroit, MI		1
Dallas - Ft. Worth, TX		4
Washington, DC		0
Atlanta, GA	Daily Vehicle Miles per Capita ↑	0
Boston, MA		0
San Diego, CA		8
Houston, TX	Daily Vehicle Miles per Capita ↑	2
Minneapolis - St. Paul, MN		2
Miami - Hialeah, FL	Persons per Square Mile ↑	6
Phoenix, AZ		7
Baltimore, MD		1
St. Louis, MO		0
Seattle, WA		1
Denver, CO		1
Tampa - St. Petersburg, FL	% of Travel Served by Freeways ↓	3
Cleveland, OH		2
San Jose, CA		0
Ft. Lauderdale - Hollywood, FL		1
Pittsburgh, PA		**0**
Milwaukee, WI		0
Norfolk - VA Beach - Newport News, VA		0
Kansas City, MO	Total Freeway Miles per Urbanized Population ↑	1
Sacramento, CA		0
Riverside - San Bernardino, CA		1
Portland - Vancouver, OR		1
San Juan, PR	Daily Vehicle Miles per Capita ↓	NA
Las Vegas, NV		1
Cincinnati, OH		4
Orlando, FL		2
San Antonio, TX		1
Buffalo - Niagara Falls, NY		1
Oklahoma City, OK		5
New Orleans, LA	Daily Vehicle Miles per Capita ↓	0
W. Palm Beach - Boca Raton - Delray Bch, FL		0
Columbus, OH		4
Memphis, TN		0
Indianapolis, IN		4
Providence - Pawtucket, RI		0
Jacksonville, FL		3
Salt Lake City, UT		2
Louisville, KY		2
Tulsa, OK		7

Note: Urbanized areas in the United States with populations above 750,000 people, listed in order of population. ↑: two standard deviations above the mean of all cities listed ↓: two standard deviations below the mean of all cities listed. Source: Federal Highway Administration (https://www.fhwa.dot.gov/ohim/onh00/onh2p11.htm) Number of Republican mayors since 1960 measures the relative political "competitiveness" of the cities on the list.

TABLE A.2

INVESTIGATING POLITICAL CYCLES ON CAR CRASHES

	More Maintenance		Entire IEP	Less Maintenance	
	(1) Oct	(2) Aug-Oct	(3) Jun-Oct	(4) Jun-Aug	(5) Jun
Panel A: Number of Crashes					
IEP * PA	0.02	0.02	-0.04	-0.09**	-0.02
	(0.07)	(0.05)	(0.04)	(0.04)	(0.08)
Mean of Crashes					7.565
Panel B: People Involved in Crashes					
IEP * PA	0.00	0.03	-0.05	-0.11*	-0.03
	(0.09)	(0.05)	(0.05)	(0.06)	(0.08)
Person Count Mean					18.49
Panel C: Count of Major Injuries					
IEP * PA	0.98*	0.37	0.19	-0.19	-0.11
	(0.51)	(0.38)	(0.27)	(0.39)	(0.37)
Mean of Major Injuries					0.160
Panel D: Heavy Truck Accidents					
IEP * PA	-0.12	-0.09	-0.34*	-0.71**	-0.26
	(0.58)	(0.24)	(0.19)	(0.28)	(0.55)
Heavy Truck Accidents Mean					0.215

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Estimates are from Poisson conditional fixed effect model, shown in Equation 1. Ward, month, and year (uninteracted) fixed effects are included in every column. Standard errors, clustered at the ward level, are shown in parentheses. DD coefficient of interest is "IEPxPA." Panel A-D change the dependent variables of interest from heavy maintenance count to various car accident outcomes. Only car crashes from 2009-2017 that occur on Pittsburgh-owned roads are included in every column.