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Elections have Consequences": Partisan Politics are Literally Killing Us

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Abstract

Presidential campaigns and election outcomes have significant health implications for voters and communities. The theoretical underpinning of this relationship is multifaceted, but a new and growing field of empirical literature strongly suggests communities that voted for the losing presidential candidate experience decreased physical and mental health under the leadership of the winning candidate. Building on this work, Centers for Disease Control (CDC), compressed mortality and election data are used across a suite of county-year fixed effects models to estimate the effect of election outcomes on mortality rates. Results suggest mortality rates increase in extremely partisan counties following election losses by as much as 3%. We discuss the potential underlying cause of this increase and suggest two mechanisms by which mortality rates are likely to increase for counties that voted for the losing Presidential candidate. The more likely mechanism is a behavioral explanation that voters experience increased isolation or anxiety after a losing election cycle.

JEL Codes: H8, I1, I18, Z0

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1. Introduction

Presidential candidates in the United States spend the better part of a year energizing potential voters and dissuading constituents from supporting other candidates. While campaigns have different tones and themes—some more unifying than others—a recent Pew Report found that the polarization of American politics and partisan antipathy are at a modern-day high (Pew 2014). Many researchers have begun to worry that hyper-partisanship will have detrimental effects on our national identity and dialogue (Green et al. 2004; Ezrow et al. 2014; Theriault 2014; Muirhead & Rosenblum 2016), since presidential candidates often espouse starkly different beliefs and ideologies (Lau et al. 2008; Polsby et al. 2008) that encourage some voters and worry others. This paper investigates whether such worries are justified by answering the following question: Do communities that voted for the losing candidate experience measurable differences in mortality rates?[1]

Given the growing partisan divide in recent decades (Gentzkow & Shapiro 2011; Pew 2014), a growing body of literature has begun investigating the effect that voting for a losing presidential candidate—referred to as *partisan loss* (PL) Pierce et al. (2016)—has on health outcomes. While literature on social determinants of health is extensive (Marmot et al. 2012; Lucyk & McLaren, 2017), there are generally two strands of literature analyzing the causes and impact of *PL* specifically. The first focuses on empirically estimating the impact of *PL* on various wellbeing measures. Although no research has empirically estimated the effect of *PL* on mortality rates specifically, which is the focus of this paper.

The second strand of literature looks at the underlying causes that may explain the impacts of PL. Generally, there are two complementary explanations for how *PL* may increase mortality rates. The first explanation is *behavioral*, where the increased isolation or anxiety levels that accompany supporting the losing candidate are correlated—and to some extent cause—poor health and potentially acute causes of death—cardiovascular events or suicide for example (Khan et al. 2002; Steptoe & Kivimäki 2012). The second mechanism is *institutional*: represented by the basic tenets of partisan theory, which suggests that voters rationally choose

[1] See Sen and Grant (1998) for a discussion on the importance of mortality rates as an economic outcome.

politicians whose policies provide them socio-economic benefits. Thus, politicians from each party attempt to enact divergent policies that benefit their supporters, potentially at the expense of those who oppose them. It is reasonable to think that such preferential policy design can result in poorer health outcomes for communities that oppose the acting administration. In this way, one cause is internal to the voter (perspectives and feelings) and the other is a result of policies that directly impact social determinants of health, and thus mortality. As such, this paper investigates the short-term impact of *PL* on mortality rates using a suite of county-year fixed effects models.

2. Literature Review

2.1 Anxiety, Stress, and Isolation

While many factors affect human health and wellbeing, researchers generally agree that negative emotions and anxiety are correlated to poorer outcomes. For example, growing evidence suggests a strong relationship between psychosocial factors (e.g. depression or chronic stress) and cardiovascular disease, particularly among those of low socioeconomic status (Elderon & Whooley 2013; Rodwin et al. 2013). Thus, it is logical that events triggering anxiety or depression indirectly lead to higher mortality rates.

PL can certainly be considered such an event. Recent work examining welfare indicators as a function of partisan electoral losses suggests that constituents who lose at the ballot box experience a quick and significant decrease in happiness after an election; such losses have a stronger effect on public wellbeing than the Newtown shootings or the Boston Marathon bombing (Pierce et al. 2016). Motyl (2014) finds that individuals who vote for the losing candidate experience decreased feelings of belonging and increased thoughts of migration. In contrast, individuals who support the current government tend to think more optimistically about their economic future (Ladner & Wlezien 2007), which may reduce anxiety, since optimism has been linked with working harder, later retirement, marriage, and increased savings (Puri & Robinson 2007).

Election results not only affect subjective measures of happiness, but have also been associated with physiological changes, where voters supporting the losing candidate experience marked drops in testosterone levels and increases in cortisol, a hormone linked to stress (Stanton et al. 2009; Blanton et al. 2012). After the 2008 elections (where Democratic candidate Barack Obama was elected), individuals who identified as conservative were more negative in emotional responses to surveys and experienced a spike in salivary cortisol levels (Blanton et al. 2012).

Researchers have begun examining the relationship between elections and health outcomes in a new and growing field of literature that suggests presidential campaigns (and other election outcomes) may have significant health implications for voters and communities. Winning candidates that support and express the ideas of historically disenfranchised groups have been associated with short-term health improvements for those communities (Williams & Mohammed 2013). By contrast, the election of officials who are hostile to socio-political groups, has been linked to increased stress-levels in those groups. In a perspectives piece, Morey (2018) discusses the mechanism by which anti-immigration politics can detrimentally affect the health of immigrant and Hispanic communities, highlighting that many of these mechanisms may be social, increasing anxiety regardless of explicit changes to policy or healthcare access.

Indeed, some data support Morey's implicit hypotheses: US states with a more exclusionary immigration policy experience higher rates of poor mental health among Latinos (Hatzenbuehler et al. 2017), although endogeneity concerns limit the causal inference of these results. Following the 2016 election, where Republican candidate Donald Trump was elected, there was a significant uptick in preterm deliveries by Latina women (Gemmill et al. 2019). While the relationship is correlative, depression and anxiety have been linked to spontaneous preterm births among African American women (Orr et al. 2002). Conversely, work by Classen and Dunn (2010) suggests suicides may decrease with PL, since such losses may improve social integration among communities.[2]

[2] It is worth noting that we attempted to replicate this study, and while point estimates are very close, they are not identical. Furthermore, results of this replication become insignificant when robust or clustered standard errors are used

Although research is limited, the current consensus in the literature suggests that campaigns and elections induce anxiety, which may result in observable, negative health outcomes, particularly for people who believe their communities are targets of hostility or discrimination (Gonzalez et al. 2018). Thus, even without policy shifts, the anxiety or social factors caused by election losses may directly affect health. Of course, empirical evidence does suggest partisan cycles and preferential partisan policies exist, which have distributional effects on human welfare if politicians enact policies that disproportionately benefit their supporters (Kauder et al. 2016; Potrafke & Roesel 2019).

2.2 Partisan and Preferential Policies

The extent that worry over voting for the losing candidate is justified largely depends on the polity of presidential leadership and the policies they create (or reverse). Theoretical and empirical work evaluating electoral-business-cycle interactions and outcomes has found mixed results, but generally suggests that incumbents can manipulate micro- and macroeconomic conditions to benefit themselves electorally (Tufte 1978; Coibion & Gorodnichenko 2015) or reward their supporters (Cox & McCubbins 1986; Curto-Grau et al. 2018; Harris & Posner 2019). The extent that this manipulation is possible depends on a) international and domestic, b) political-economic, and c) institutional and structural contexts (Franzese 2002).

Although the degree of manipulation may vary across contexts, partisan theory suggests that as part of their electoral-seeking behavior, competing political parties cultivate relationships with different voting blocs by nurturing reputations for policy-making that favors those groups. As a result, counties that favored the winning candidate will disproportionally benefit under their leadership.[3] Indeed, recent work by Reingewertz and Baskaran (2019) suggests that Presidents provide more federal outlays to districts represented by their co-partisans.

Some of these policies directly affect socio-demographic groups, while others influence macroeconomic conditions that indirectly favor particular constituents. For example, social policies like the legalization of same-sex marriage or expansion of Medicare have specific targeted populations. By comparison, policies that affect interest rates or income taxes may not

[3] Note, that we omit a common discussion of the median-voter theory (Downs 1957) and partisan theory (Alesina, 1988) for brevity, and accept the "overwhelming empirical evidence [that] shows legislators regularly take positions that diverge significantly from the preferences of the median voter in their districts" (Gerber & Lewis 2004).

target specific beneficiaries but affect macroeconomic conditions that have distributional impacts across partisan and socioeconomic groups. For the majority of the 20th century (although somewhat different in recent history), a clear distinction of left- and right- party policy was the relative importance placed on inflation or unemployment. Leftist parties accept higher inflation to obtain lower unemployment and higher growth; rightist parties tolerate higher unemployment and lower growth to obtain lower inflation (Franzese 2002). These policy tradeoffs have implications for socio-economic groups, where those at the low end of occupational and income hierarchies are disproportionately hurt by unemployment and recessions that are only partially offset by tax-and-transfer systems (Hibbs 1987).

Health policies enacted by presidential administrations also have direct distributional impacts. For example, the Affordable Care Act (ACA) significantly increased health insurance enrollment (Courtemanche et al. 2017). Among young adults, Barbaresco et al. (2015) found the ACA increased the probability of having health insurance, a primary care doctor, excellent self-assessed health, and a reduction in body mass index. Over the last 50 years the use of federal funds to sponsor Community Health Centers reduced mortality by 2% among individuals older than 50 (Bailey & Goodman-Bacon 2015), while Medicare has led to a sharp increase in medical services for those 65 and older (Card *et al*. 2005). These results have obvious implications for health outcomes and mortality, but agricultural, environmental, infrastructure, or defense policies also have distributional health impacts across locations and socio-economic groups (Rate & Person- Years 1990; Lester 1993; Osterberg & Wallinga, 2004; Aguilera et al. 2007; Sperling & Ramaswami, 2013). These policies enacted under partisan administrations may affect mortality, if only indirectly.

While policy has obvious implications for affecting distributional health outcomes, it is difficult to separately identify the direct effect of policy from the constituent's perspectives on that policy, and the politicians who enacted it. As such, we reiterate that the following analysis investigates the effect of presidential elections on mortality rates of communities who voted for or against that President, but it does not make claims about the underlying mechanisms of this relationship. Indeed, it is likely that both mechanisms are occurring simultaneously and cannot be separately identified without experimentation.

3. Data and Estimation

Estimating the effect a particular leader or election has on the economy or constituents is complicated by potential reverse causality. Simply put, voters' expectations about the future (whether accurate or not) may affect both who wins the election and how future policies manifest. This concern has been thoroughly voiced in the literature, particularly with respect to interest rates and unemployment (Franzese 2002). While these concerns are valid in many analyses, using presidential election results as an explanatory variable in county-level mortality rates helps ameliorate concerns of endogeneity for two reasons. First, individual counties have little effect on the election results, such that the ultimate winning candidate is largely exogenous to the voting behavior of partisan counties. For example, in Bronx County, NY approximately 90% of votes cast in Presidential elections are for Democratic candidates. In elections where Democrats win *PL* would be very low; in elections where a Republican wins the loss score would be large, but in either case Bronx voters have little influence on the final electoral outcome.

Second, at the national level (and in swing counties), Republican and Democratic candidates share about 50% of the vote, such that the ultimate winner is largely uncertain and independent of particular counties. Thus, counties experience quasi-experimental shocks to *PL* whenever elections are essentially a coin toss. This logic is similar to Lee et al.'s argument of close elections as a proxy for random assignment (2004). In fact, two of the five presidential elections in our sample had unexpected results,[4] where the candidate who won the popular vote ultimately lost the election. These unexpected election outcomes lessen endogeneity concerns over spurious correlations between economic or political expectations.

3.1 Data

To test our hypotheses, primarily that voting for a losing candidate increases (total, cardiovascular, and self-harm) mortality rates, a suite of models were estimated using total number of deaths and age-adjusted crude rates (occurrence per 100,000) for males and females, ages 20 to 69, in each county, between the years 1999 and 2017. As is common in the literature,

[4] Beyond winning the popular vote, Al Gore and Hillary Clinton were both favored based on the odds given by common gambling websites and some national polls.

we run separate models for men and women because they have significantly different mortality distributions, particularly for suicide and cardiovascular causes of death (COD). Our primary focus is on total mortality rates, but more acute CODs like cardiovascular and suicide are estimated individually because these conditions are more sensitive to acute changes in economic conditions, compared to long-term illnesses like cancer (Brainerd 2001). The years included in our study are coded with the tenth revision of the International Classification of Diseases (ICD-10), which began in 1999. Comparability between ICD-10 and ICD-9 complicates classification since the National Vital Statistics System acknowledges the discontinuity in trend is substantial for some CODs. Thus, we limit the analysis to years with ICD-10 coding. This temporal range provides sufficient variation as it includes the results from five elections and both Democratic and Republican presidencies. Crude rates were calculated using detailed mortality data from the Centers for Disease Control (CDC).

Voting data include county-level election results as compiled by David Leip in the Atlas of U.S. Presidential Elections (2019). We use these data to compile several explanatory variables meant to capture PL and use different combination of these variables in the models specified below. These include a continuous (PL_c), discrete (PL_d), PL metric, as well as a dummy variable to indicate extremely partisan counties (EP). The continuous variable is calculated as the ratio of total votes for the losing candidate over the sum of total votes for a major party candidate.[5] The discrete variable is calculated as 1 if more than 50% of the votes cast for a major party candidate were for the losing candidate and 0 otherwise. Extreme partisanship is calculated as 1 if more than 65% or fewer than 35% of the votes cast for a major party candidate were for the losing candidate and a 0 otherwise.

A complication in estimating models with an annual time step is the timing of elections. In election years, calculating the PL term is problematic because ten months exist before, and two months exist after, the election. To avoid weighting complications, election years were dropped from the sample for Models 1-4.[6] PL_c is calculated as a continuous variable between 0 and 1

[5] Note that lumping left and right parties together does not affect our results, but this version is not presented in our results as the policies of third-party candidates do not consistently align for or against the policies of the presidents' party. Moreover, logic dictates that voters supporting third-party candidates had no expectation of winning.

[6] Note that the omission of election years does not qualitatively change the results, and only marginally affects point estimates and overall model fit.

which represents the proportion of individuals in a county that vote for the losing candidate. This variable therefore remains constant across the 4-year term of the elected president. As such, each county is assigned 5 unique values to reflect the relative PL experienced by the county for each election cycle across for each year in the sample.

In combining and cleaning these datasets, some counties and one state are completely omitted from our analysis. Alaska's boroughs could not be mapped consistently across voting and CDC datasets. Several additional counties were omitted if FIPS boundaries or codes changed across the years in our sample. Despite these omissions, the dataset remains large with 3026 distinct counties across 49 states and 18 years.

3.2 Models

Three measures of mortality rates (separated by cause of death) were included as dependent variables across a suite of regressions: total mortality, suicide, and cardiovascular. Because mortality rates are necessarily positive (or zero) and skewed left with a long right tail, each equation below is estimated using total count[7], crude rate, and a $\sinh^{-1}(y_{it})$ transformation as the dependent variable. A fixed effects model is used to control for county and year fixed effects, which should absorb any annual or geographic differences. Thus, the simplest model can be written as:

$$y_{it} = \alpha_i + b_t + \beta PL_{it} + \epsilon_{it} \tag{1}$$

Where y_{it} is the mortality rate (total, suicide, or cardiovascular), α and b are fixed effects terms for county and year respectively, β is the coefficient of interest, and ϵ is a stochastic error term. Counties are indexed by i, and years are indexed by t. While the above model specification allows for intercept differences in year and county, it may be too restrictive if factors influencing mortality vary across states over time. In this case, the model must allow for interactions of year and state factor variable and can be written as:

[7] Mortality count data are estimated as a Poisson regression, using total count as the dependent variable with the basic form: $p(y|x;\beta) = \frac{\left(e^{y\beta'} e^{-e^{\beta' x}}\right)}{y!}$. The presentation of these models are excluded from the main text for succinctness but estimated with Stata's pseudo-Poisson estimated command, ppmlhdfe (Correia et al. 2019), and reported in the Results Section.

$$y_{it} = \alpha_i + \sum_{j=1}^{49} \sum_{t=1}^{14} \rho_{jt} s_j b_t + \beta PL_{it} + \epsilon_{it} \quad (2)$$

Where s_j is a set of dummy variables for each state and ρ are interaction specific coefficients to be estimated. Equation 2 is preferred because it uses over 3,600 dummy variables to control for geographic and temporal variation. However, both Equations 1 and 2 assume a linear and constant marginal effect of PL_c, which may be unrealistic in the presence of thresholds or non-linearities across election cycles or PL. Equations 3-5 also examine the relationship of *PL* and mortality using complementary, but different, underlying data-generating processes.

The third approach uses a pseudo-difference-in-difference to estimate the effect of *PL* in extremely partisan counties, where we remove variation of losing ($PL_{d,it}$) and being in an extremely partisan county (EL_{it}), to focus on the interaction of these two effects:

$$y_{it} = \alpha_i + \sum_{j=1}^{49} \sum_{t=1}^{14} \rho_{jt} s_j b_t + \theta_1 PL_{d,it} + \theta_2 EL_{it} + \tau EL_{it} PL_{d,it} + \epsilon_{it} \quad (3)$$

Where $\theta' s$ and τ are coefficients to be estimated, and τ is the effect of losing in extremely partisan counties.

After any election, a county will either be a winner or loser, such that every new election will have counties either moving from being partisan losers to partisan winners, partisan winners to partisan losers, or maintaining their status as winners or losers across elections. Thus, three dummy variables are created: winners to losers (WL_{it}), losers to winners (LW_{it}), and losers to losers (LL_{it}). Note that a binary variable for winners to winners is omitted for model identification and should be considered the baseline to which coefficients are compared:

$$y_{it} = \alpha_i + \sum_{j=1}^{49} \sum_{t=1}^{14} \rho_{jt} s_j b_t + \gamma_1 LL_{it} + \gamma_2 WL_{it} + \gamma_3 LW_{it} + \epsilon_{it} \quad (4)$$

The last model is used to investigate the temporal relationship of *PL* and mortality within an election cycle. Thus, an interaction term is created by multiplying $PL_{d,it}$ with a set of dummy variables representing years since an election such that the model can be written as:

$$y_{it} = \alpha_i + \sum_{j=1}^{49} \sum_{t=1}^{14} \rho_{jt} s_j b_t + \sum_{c=0}^{3} \vartheta_c Y_c PL_{d,it} + \epsilon_{it} \quad (5)$$

Where Y_c are dummy variables for each year after an election, indexed by $c \in [0,3]$.

Equations 1-5 are estimated using population-weighted least squares, as is common when observational units have substantially different populations (Wolfers 2006; Solon 2015) and hypothesis testing is done using standard errors clustered on the county election cycle. While this suite is not exhaustive, each model is included because limited theory exists to dictate this structural relationship.

3.3 Summary Statistics

A preliminary exposition of the data supports our use of fixed effects, as we observe distinct temporal and spatial trends in all three mortality measures. The data include 18 years (although 4 election years are omitted in most models) and 3,026 counties. While overall mortality levels differ across men and women, general trends are similar. Figure 1 presents the national average crude rates by causes of death (COD) and sex. For males 20 to 69, mortality rates for all COD (right axis) range from approximately 540 to 620 per 100,000 with an increase in recent years. Mortality rates for women of the same age ranges from 360 to 400 per 100,000. Mortality rates for major cardiovascular causes of death (left axis) shows a slight u shape, with years of decline before a more recent increase. By comparison, suicide has steadily increased across the years in our sample for both men and women.

FIGURE 1

The distribution of PL_c is roughly normal, with a mean of 0.48, standard deviation of 0.17, and a range between 0.03 and 0.97, suggesting that some counties experience drastic PL swings from one administration to another, but most experience a PL_c change of less than 0.34 across elections.

4. Results

Results from Equations 1-5 are reported separately for underlying causes of death—total, cardiovascular, and suicide. Overall model fit is exceedingly high ($R^2 > 0.9$ for total mortality models), but given the large set of fixed effects, this is not surprising. Results are qualitatively consistent across all causes of death and model specifications.

Equations 1-2 are used to estimate the direct relationship between PL_c and mortality. Results suggest a statistically significant and meaningful relationship. For a 10% increase in PL_c results suggest total mortality will increase by 1% for both men and women (Table 2 Column 2). A similar increase is observed across all CODs included in the analysis (Table 2 Columns 5,8). While men have significantly higher mortality rates across all CODs, the marginal effects of *PL* are similar across genders. However, the point estimate for women's mortality caused by cardiovascular events is noticeably higher, suggesting a 10% change in PL_c may lead to a 1.4% increase in cardiovascular related deaths for females, but only a 0.6% increase for males (Table 2 Column 5).

Equations 3-5 assume different underlying data-generating processes but indicate qualitatively similar effects of *PL* on mortality rates. Results from estimating Equation 3 suggest extremely partisan counties experience increases in crude mortality rates of 4% for both men and women in years where they have lost the previous presidential election (Table 3, Column 1).[8] However, conditional on winning the most recent election, extremely partisan counties have lower mortality rates (-12.5/100,000 or 2% for men and -4.6/100,000 or 2% for women) compared to their less-partisan fellow winners (Table 3, Columns 1 & 2). This model also suggests that the change in mortality rate for losing (PL_d) as a binary outcome has a weaker (or no) effect on mortality for moderate counties. Indeed, this finding supports results from Models 1-2, which also suggest mortality rates increase with higher degrees of *PL*.

Model 4 estimates the relationship between *PL* and mortality, but explicitly estimates four possible election outcomes, losing counties lose again, winning counties lose the most recent election, losing counties win the most recent election, and winning counties win again. The model suggests a similar effect of losing or winning the most recent election regardless of the prior election results, although point estimates are slightly larger for counties that lost sequential elections. For example, losing counties that lose the most recent election see an increase in total mortality rates of 11.2/100,000 or 3% for men and 7.3/100,000 or 3% for women (Table 4 Columns 1 & 2), whereas counties that recently lost but won the previous election see rates increase by 6.9/100,000 or 1% for men and 5.7/100,000 or 2% for women. A similar, but

[8] Marginal effects of dummy variables are calculated using the Halvorsen and Palmquist (1980) approximation method described by Bellemare and Wichman (2019).

smaller and less significant, effect is observable for cardiovascular and self-inflicted mortality rates (Table 4 Columns 4 & 7). There is little difference in counties that move from losing to winning compared to those that win sequential elections (a 1% decrease in total mortality, $p < 0.05$).

Model 5 suggests similar results as 1-4, but allows the effect of PL_d to vary within an election cycle, based on the years since the election occurred. Using winning in the election year as a baseline, a significant effect is observed for *PL* in each subsequent year. Interestingly, there is no effect on mortality in election years. The lack of significance in election years is hypothesized to exist for two reasons, although neither are formally tested herein. Most likely, the non-effect of *PL* in an election year is a function of the temporal incongruity of our data, where election years have months both before and after an election, and therefore 10 months of an election year where counties support the current election winner, may be assigned a losing score. It is also possible that election years are fundamentally different since salient hope (or despair) over the impending election will likely interact with any effects of *PL*. Notably, we also observe a marked decline in mortality for counties that will ultimately lose the election in an election year. While overall results refute earlier work by Classen and Dunn (2010) who suggest election losses reduce suicide, we do observe a similar phenomenon in election years. In election years, counties supporting the eventual loser exhibit a lower mortality rate than counties that support the eventual winner. This result (similar to Classen and Dunn's finding) is perplexing since ten months of the election year occur before *PL* is realized, yet counties that will eventually lose, experience a significant decrease in mortality that year.

4.1 Additional Robustness Checks

Although Equations 2-5 all assume a different structural relationship of *PL* and mortality, consistent qualitative results strongly suggest a significant and meaningful effect. To provide additional robustness checks and to help identify the appropriate structural relationship, three additional approaches are considered.

First, a placebo treatment is created and used in Equations 2. As a placebo, each election-county cycle is randomly assigned partisan loss scores (PL_c, PL_d) across the sample and estimated with these placebo scores in place of actual *PL* scores. While placebo treatments are imprecise, they provide at least some measure that informs the validity of the underlying estimation strategy

(Clemens 2017). For Model 2, coefficient estimates on PL placebo treatments prove insignificant ($p > 0.1$). Although placebo tests are not conclusive, they bolster the argument that PL effects are real, and not simply an artifact of a larger dataset or unobserved phenomenon.

Next, PL_c is removed from Equation 2 such that mortality is regressed only on the state-year and county fixed effects, but no metric of PL. The residuals from this estimation are then plotted against binned PL_c. A strong positive relationship is visible in Figure 2, which suggests the exclusion of PL_c from the model leads to an over prediction in counties with low levels of PL, and an under prediction in counties with high levels of PL.

FIGURE 2

Moreover, the continuity of the line—or lack of discontinuity— at 0.5 supports the use of a continuous PL score rather than a discrete loss metric, since at this point a county is evenly divided between winners and losers. Lastly, this figure provides weak evidence that the relationship between PL_c and mortality is not linear, since counties with very low (or high) PL_c are substantially over (or under) estimated when PL_c is excluded from the model. Figure 2 presents two best-fit lines regressing residuals on to PL_c, where the 3rd order polynomial function provides a slight fit improvement to a simple linear function.

Lastly, PL is treated as a dose-response function, where county-years are "treated" when $PL_d = 1$ and untreated otherwise. The "dose" is the degree of loss (PLc) normalized between 0 and 100. The full model is omitted for succinctness, but identical to the unconfounded model presented by Cerulli (2006) where a vector of dummies for county and year are included as covariates. The Dose-Response is specified as a 3rd degree polynomial function to allow for changes in the first and second order derivatives.

FIGURE 3

Figure 3 presents predicted mortality response due to PL, when such losses are assumed to have a "treatment-dose effect". Consistent with Models 1-5, mortality increases with PL at an increasing rate. These results further support the possible erroneous linear assumption of Models 1-2, such that increased mortality may be concentrated in extremely partisan counties (consistent with Model 3 results).

5. Discussion

A clear finding from this analysis is the relationship between partisan election results and mortality rates. The data broadly suggest that mortality rates increase by 0.7% for every 10% of the population that votes for the losing candidate. Considering the large partisan swings in some counties across elections, this effect is meaningful and suggests increased mortality rates of over 3% for extremely partisan counties (where PL may jump from 0.1 to 0.9 from one election to another). Careful interpretation of our results is necessary, as well as a consideration of causality. In this context, there is significant reason to believe that election results are largely exogenous to the individual, such that the response in mortality rates can be properly attributed to partisan loss. However, it is also true that simply losing a partisan election is unlikely to have a direct mechanistic link, such that claiming one causes the other may be misleading. Instead, we posit that losing an election may influence mortality through some combination of realized partisan policy and feelings of anxiety associated with increased feelings of alienation, helplessness and normalness as defined by defined by Seeman 1959.

Despite the strength of our statistical results, this study has several limitations. First, we are limited by the data collected, and are unable to gain additional insights into individual characteristics and policies that may help elucidate particular mechanisms for mortality rate increases. Second, we are limited to annual data in this analysis and therefore miss any acute responses to the election, particularly the months of November and December. Observing changes immediately following the election would help differentiate the effect of internal anxiety or depression as a function of election results from the effects of partisan policy, since the election occurs two months before a President can affect policy.

To the extent that this mortality response is due to policy changes, our results add to the evidence that median-voter theory does not sufficiently describe political behavior. If few policy differences exist across winning and losing candidates, as median-voter theory suggests, mortality rates should not change based on election outcomes. Although we do not explicitly evaluate the creation of partisan policy, the increase in mortality rates for counties that do not support the president may suggest that such partisanship exists.

To the extent that social alienation and anxiety drive the mortality responses identified herein, a presidential candidate may help ameliorate such feelings through messages of unity and bipartisanship. Indeed, discrimination has significant impacts on a range of health outcomes, including blood pressure, cholesterol, BMI and self-assessed general health (Johnston & Lordan 2012). Combining our findings with previous work strongly suggests that messages of unity from presidential winners may significantly improve health outcomes.

Results also highlight the existence of a mortality cycle, corresponding to electoral victories and losses. While the results presented herein are robust across numerous specifications, there is a significant need to elucidate the relationship of partisan loss, the social determinants of health, and actual health outcomes. Future work should investigate the interaction of national politics and local communities through the lens of social alienation and anxiety, a topic that is particularly relevant given the increased geographic segregation of liberals and conservatives (Motyl et al. 2014). This additional work would provide robustness to our own findings and may help with causal interpretation. It may also suggest that the winner-take-all system we use in partisan elections may have significant unacknowledged costs for supporters of the losing candidate, which may be exacerbated by the increased geographic segregation of liberals and conservatives (Martin et al. 2018; Kaplan et al. 2019).

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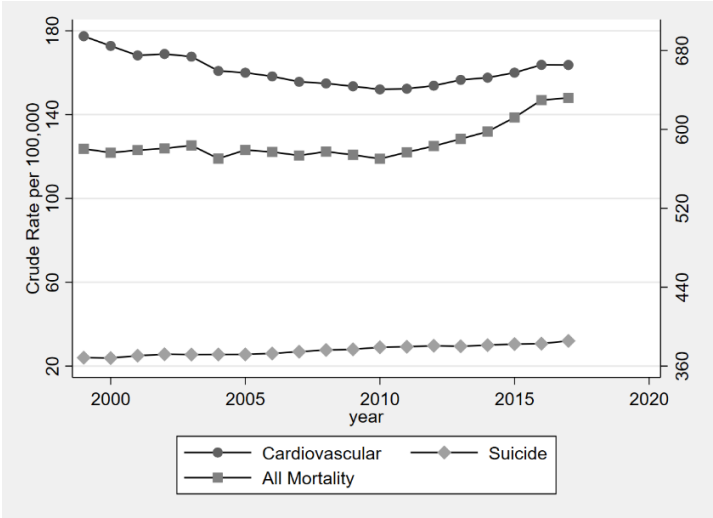
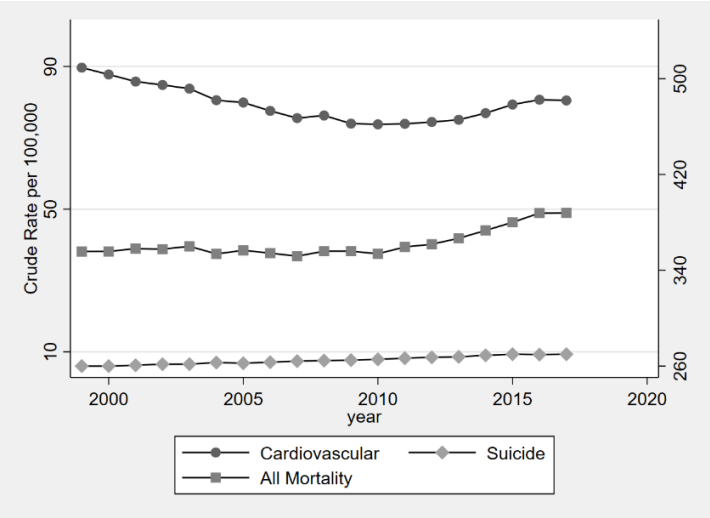
FIGURE 1: Mortality Trends by Cause of Death





Mortality rate adjusted for weighted population of sample (does not include Alaska). Axes' scales differ by sex.

FIGURE 2: Residual Plot of Auxiliary Regression

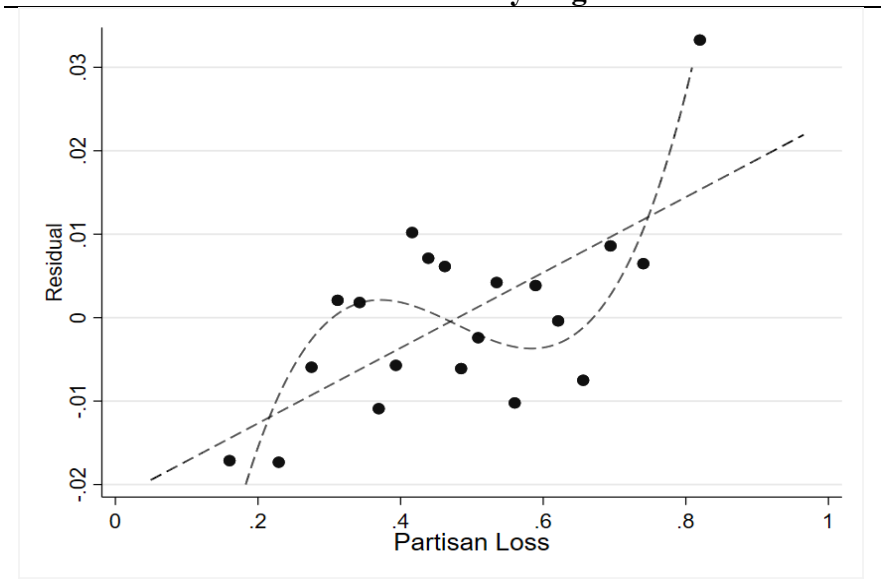
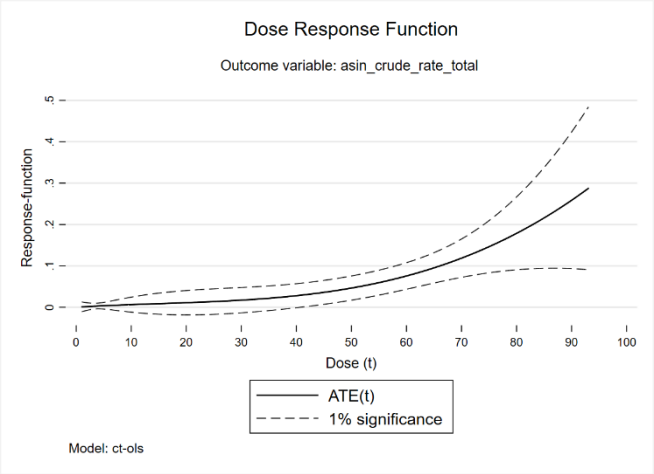
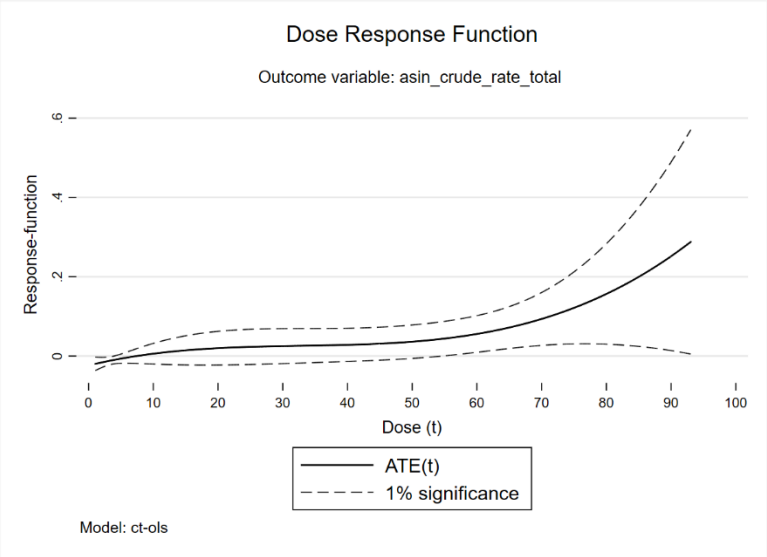


FIGURE 3: Average Treatment Effects (PL) in Dose-Response Model



Men 20-69



Women 20-69

Table 1: Equation 1

VARIABLES	(1) Total y	(2) Total $\sinh^{-1}(y_{it})$	(3) Total Poi.	(4) Cardio. y	(5) Cardio. $\sinh^{-1}(y_{it})$	(6) Cardio. Poi.	(7) Suicide y	(8) Suicide $\sinh^{-1}(y_{it})$	(9) Suicide Poi.
				Men					
PL	48.54***	0.09***	0.10***	8.38***	0.07***	0.06***	1.83***	0.05**	0.09***
	(9.68)	(0.02)	(0.01)	(2.07)	(0.01)	(0.01)	(0.48)	(0.02)	(0.02)
Constant	565.03***	6.96***	6.36***	157.56***	5.64***	5.08***	26.70***	3.82***	3.10***
	(4.67)	(0.01)	(0.01)	(1.03)	(0.01)	(0.01)	(0.24)	(0.01)	(0.01)
Observations	42,168	42,168	42,168	42,168	42,168	42,154	42,168	42,168	41,832
R-squared	0.92	0.89		0.86	0.70		0.44	0.36	
				Women					
PL	36.42***	0.12***	0.11***	9.24***	0.15***	0.12***	0.29	0.04	0.08***
	(5.52)	(0.02)	(0.01)	(1.36)	(0.02)	(0.01)	(0.23)	(0.03)	(0.03)
Constant	346.17***	6.46***	5.94***	75.26***	4.83***	4.47***	7.48***	2.37***	2.04***
	(2.72)	(0.01)	(0.01)	(0.68)	(0.01)	(0.01)	(0.12)	(0.02)	(0.02)
Observations	42,168	42,168	42,168	42,168	42,168	41,720	42,168	42,168	39,032
R-squared	0.91	0.81		0.83	0.63		0.26	0.38	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects are omitted for succinctness

Table 2: Equation 2

VARIABLES	(1) Total y	(2) Total $\sinh^{-1}(y_{it})$	(3) Total Poi.	(4) Cardio. y	(5) Cardio. $\sinh^{-1}(y_{it})$	(6) Cardio. Poi.	(7) Suicide y	(8) Suicide $\sinh^{-1}(y_{it})$	(9) Suicide Poi.
				Men					
PL	52.76***	0.10***	0.10***	9.57***	0.06***	0.06***	2.74***	0.11***	0.09***
	(7.85)	(0.01)	(0.01)	(1.94)	(0.01)	(0.01)	(0.51)	(0.02)	(0.02)
Constant	562.99***	6.95***	6.36***	156.99***	5.65***	5.08***	26.26***	3.79***	3.10***
	(3.79)	(0.01)	(0.01)	(0.95)	(0.01)	(0.01)	(0.25)	(0.01)	(0.01)
Observations	42,168	42,168	42,168	42,168	42,168	42,154	42,168	42,168	41,832
R-squared	0.93	0.89		0.86	0.71		0.45	0.37	
				Women					
PL	32.65***	0.10***	0.11***	10.16***	0.14***	0.12***	0.61**	0.15***	0.08***
	(4.26)	(0.01)	(0.01)	(1.18)	(0.02)	(0.01)	(0.24)	(0.04)	(0.03)
Constant	347.99***	6.46***	5.94***	74.81***	4.84***	4.47***	7.32***	2.32***	2.04***
	(2.08)	(0.01)	(0.01)	(0.58)	(0.01)	(0.01)	(0.12)	(0.02)	(0.02)
Observations	42,168	42,168	42,168	42,168	42,168	41,720	42,168	42,168	39,032
R-squared	0.92	0.82		0.84	0.64		0.28	0.40	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects are omitted for succinctness

Table 3: Equation 3

VARIABLES	(1) Total y	(2) Total $\sinh^{-1}(y_{it})$	(3) Total Poi.	(4) Cardio. y	(5) Cardio. $\sinh^{-1}(y_{it})$	(6) Cardio. Poi.	(7) Suicide y	(8) Suicide $\sinh^{-1}(y_{it})$	(9) Suicide Poi.
				Men					
$EL * PL_d$	24.49***	0.04***	0.04***	5.40***	0.04***	0.03***	1.44***	0.06***	0.05***
	(4.08)	(0.01)	(0.01)	(1.08)	(0.01)	(0.01)	(0.30)	(0.01)	(0.01)
EL	-12.54***	-0.02***	-0.04***	-2.38***	-0.02**	-0.03***	0.02	0.01	-0.02**
	(2.79)	(0.00)	(0.00)	(0.90)	(0.01)	(0.01)	(0.26)	(0.01)	(0.01)
PL_d	1.49	0.00*	0.00	-0.31	-0.00	-0.00	0.17	0.01	0.00
	(1.60)	(0.00)	(0.00)	(0.54)	(0.00)	(0.00)	(0.15)	(0.01)	(0.01)
Constant	588.54***	7.00***	6.41***	161.78***	5.68***	5.12***	27.31***	3.82***	3.14***
	(1.29)	(0.00)	(0.00)	(0.43)	(0.00)	(0.00)	(0.12)	(0.01)	(0.00)
Observations	42,168	42,168	42,168	42,168	42,168	42,154	42,168	42,168	41,832
R-squared	0.93	0.89		0.86	0.71		0.45	0.37	
				Women					
$EL * PL_d$	13.31***	0.04***	0.04***	3.92***	0.05***	0.05***	0.65***	0.10***	0.08***
	(2.27)	(0.01)	(0.01)	(0.68)	(0.01)	(0.01)	(0.14)	(0.02)	(0.02)
EL	-4.68**	-0.01**	-0.03***	-0.12	-0.00	-0.02**	-0.31**	-0.03	-0.06***
	(1.87)	(0.01)	(0.01)	(0.60)	(0.01)	(0.01)	(0.13)	(0.02)	(0.02)
PL_d	2.83***	0.01***	0.01***	1.31***	0.02***	0.01***	-0.17**	-0.00	-0.02**
	(1.05)	(0.00)	(0.00)	(0.36)	(0.01)	(0.00)	(0.08)	(0.01)	(0.01)
Constant	362.25***	6.51***	6.00***	78.67***	4.89***	4.52***	7.70***	2.39***	2.10***
	(0.86)	(0.00)	(0.00)	(0.29)	(0.00)	(0.00)	(0.06)	(0.01)	(0.01)
Observations	42,168	42,168	42,168	42,168	42,168	41,720	42,168	42,168	39,032
R-squared	0.92	0.82		0.84	0.64		0.28	0.40	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects are omitted for succinctness

Table 4: Equation 4

VARIABLES	(1) Total y	(2) Total $\sinh^{-1}(y_{it})$	(3) Total Poi.	(4) Cardio. y	(5) Cardio. $\sinh^{-1}(y_{it})$	(6) Cardio. Poi.	(7) Suicide y	(8) Suicide $\sinh^{-1}(y_{it})$	(9) Suicide Poi.
				Men					
LL	11.18***	0.03***	0.01***	2.57***	0.02***	0.01	0.92***	0.04***	0.01**
	(2.15)	(0.00)	(0.00)	(0.70)	(0.00)	(0.00)	(0.19)	(0.01)	(0.01)
WL	6.89***	0.01***	0.02***	1.48**	0.01	0.01**	0.35	0.02*	0.01*
	(2.36)	(0.00)	(0.00)	(0.75)	(0.01)	(0.00)	(0.22)	(0.01)	(0.01)
LW	-0.08	0.00	-0.01**	1.62**	0.02***	0.00	0.23	0.01	-0.01
	(2.18)	(0.00)	(0.00)	(0.74)	(0.00)	(0.00)	(0.22)	(0.01)	(0.01)
Constant	584.65***	6.99***	6.40***	160.39***	5.67***	5.11***	27.27***	3.82***	3.14***
	(1.39)	(0.00)	(0.00)	(0.43)	(0.00)	(0.00)	(0.12)	(0.01)	(0.00)
Observations	42,168	42,168	42,168	42,168	42,168	42,154	42,168	42,168	41,832
R-squared	0.93	0.89		0.86	0.71		0.45	0.37	
				Women					
LL	7.29***	0.03***	0.01***	2.95***	0.05***	0.03***	0.17*	0.03**	0.01
	(1.41)	(0.00)	(0.00)	(0.46)	(0.01)	(0.01)	(0.10)	(0.01)	(0.01)
WL	5.86***	0.02***	0.02***	2.59***	0.03***	0.03***	-0.13	0.01	-0.01
	(1.57)	(0.00)	(0.00)	(0.51)	(0.01)	(0.01)	(0.11)	(0.02)	(0.01)
LW	-0.10	0.00	-0.01**	1.18**	0.02**	0.01	-0.05	-0.00	-0.02
	(1.49)	(0.00)	(0.00)	(0.51)	(0.01)	(0.01)	(0.11)	(0.02)	(0.01)
Constant	360.96***	6.50***	5.99***	78.27***	4.88***	4.51***	7.62***	2.38***	2.09***
	(0.90)	(0.00)	(0.00)	(0.28)	(0.00)	(0.00)	(0.06)	(0.01)	(0.01)
Observations	42,168	42,168	42,168	42,168	42,168	41,720	42,168	42,168	39,032
R-squared	0.92	0.82		0.84	0.64		0.28	0.40	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects are omitted for succinctness

Table 5: Equation 5

VARIABLES	(1) Total y	(2) Total $\sinh^{-1}(y_{it})$	(3) Total Poi.	(4) Cardio. y	(5) Cardio. $\sinh^{-1}(y_{it})$	(6) Cardio. Poi.	(7) Suicide y	(8) Suicide $\sinh^{-1}(y_{it})$	(9) Suicide Poi.
				Men					
$PL_d * Y0$	-3.67	0.00	0.01	-1.58	-0.01	0.00	-0.65	-0.01	-0.01
	(9.14)	(0.01)	(0.01)	(2.66)	(0.01)	(0.01)	(0.44)	(0.01)	(0.01)
$PL_d * Y1$	6.63***	0.01***	0.02***	0.23	-0.00	0.01**	0.41*	0.02	0.02***
	(2.18)	(0.00)	(0.00)	(0.71)	(0.00)	(0.00)	(0.23)	(0.01)	(0.01)
$PL_d * Y2$	12.88***	0.03***	0.03***	1.95**	0.01***	0.01***	0.48**	0.02**	0.01
	(2.20)	(0.00)	(0.00)	(0.80)	(0.00)	(0.00)	(0.24)	(0.01)	(0.01)
$PL_d * Y3$	6.78***	0.02***	0.01**	1.44**	0.01**	0.00	0.55**	0.02**	0.01
	(2.20)	(0.00)	(0.00)	(0.73)	(0.00)	(0.00)	(0.22)	(0.01)	(0.01)
Constant	586.54***	6.99***	6.41***	161.52***	5.67***	5.11***	27.47***	3.83***	3.14***
	(1.71)	(0.00)	(0.00)	(0.52)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)
Observations	57,228	57,228	57,228	57,228	57,228	57,228	57,228	57,228	57,057
R-squared	0.89	0.88		0.83	0.70		0.43	0.36	
				Women					
$PL_d * Y0$	-2.31	0.00	0.01	-0.33	-0.01	0.00	-0.44***	-0.03*	-0.04**
	(5.91)	(0.01)	(0.01)	(1.51)	(0.01)	(0.01)	(0.16)	(0.02)	(0.02)
$PL_d * Y1$	4.20***	0.01***	0.02***	1.52***	0.01	0.02***	-0.12	0.00	-0.01
	(1.41)	(0.00)	(0.00)	(0.45)	(0.01)	(0.01)	(0.12)	(0.02)	(0.01)
$PL_d * Y2$	8.07***	0.03***	0.03***	2.71***	0.04***	0.03***	0.01	0.03	0.00
	(1.45)	(0.00)	(0.00)	(0.51)	(0.01)	(0.01)	(0.13)	(0.02)	(0.02)
$PL_d * Y3$	6.88***	0.02***	0.02***	2.20***	0.04***	0.02***	0.13	0.03*	0.01
	(1.48)	(0.00)	(0.00)	(0.47)	(0.01)	(0.01)	(0.11)	(0.02)	(0.01)
Constant	362.25***	6.51***	5.99***	79.26***	4.89***	4.52***	7.67***	2.38***	2.09***
	(1.10)	(0.00)	(0.00)	(0.30)	(0.00)	(0.00)	(0.04)	(0.01)	(0.00)
Observations	57,228	57,228	57,228	57,228	57,228	56,943	57,228	57,228	54,378
R-squared	0.87	0.81		0.81	0.63		0.27	0.39	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
are omitted for succinctness