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Disastrous discretion: Ambiguous decision situations foster political favoritism

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DISASTROUS DISCRETION

AMBIGUOUS DECISION SITUATIONS FOSTER POLITICAL FAVORITISM

Stephan A. Schneider* and Sven Kunze**

February 9, 2021

Abstract: Allocation decisions are vulnerable to political influence, but it is unclear in which situations politicians use their discretionary power in a partisan manner. We analyze the allocation of presidential disaster declarations in the United States, exploiting the spatiotemporal randomness of all hurricane strikes from 1965–2018. We show that biased declaration behavior is not politically affordable if a disaster is either very strong or weak, when relief provision is clearly necessary or not. However, in ambiguous situations, after medium-intensity hurricanes, presidents favor areas governed by their co-partisans. Our nonlinear estimations demonstrate that this hump-shaped alignment bias exceeds average estimates up to eightfold.

Keywords: disaster relief, distributive politics, hurricanes, natural disasters, nonlinearity, party alignment, political influence, political economy.

JEL-Classification: D72, H30, H84, P16, Q54.

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1 Introduction

Natural disasters constitute severe negative shocks for people in affected regions. But disasters also create opportunities for politicians. They can show their leadership skills in the light of a catastrophic event that attracts substantial public attention and may be able to use disaster relief as an instrument for strategic fund distribution. This raises concerns that political factors undermine an efficient allocation of disaster assistance.

In this paper, we use random spatiotemporal variation in physical hurricane intensities to identify a nonlinear political bias in U.S. federal disaster declarations. Previous analyses of various political-economic settings provide evidence for different forms of home-region favoritism (e.g., Burgess et al., 2015; Carozzi & Repetto, 2016; Gehring & Schneider, 2018; Hodler & Raschky, 2014) and increased government spending to politically aligned areas (e.g., Berry et al., 2010; Brollo & Nannicini, 2012; Curto-Grau et al., 2018; Fiva & Halse, 2016).¹ However, little is known about whether politicians generally act in a self-interested manner or whether only specific situations foster behavior that results in biased allocations. We argue that political-economic relationships are nonlinear, being over-proportionally strong in ambiguous situations that allow politicians to make targeted use of their discretion (cf. Durante & Zhuravskaya, 2018; Hodler et al., 2010). Studying the political reaction to hurricanes, we show that the strength of the political bias in executive decision-making on whether to provide disaster relief depends on the degree to which a specific event presents a favorable opportunity for strategic behavior. To the best of our knowledge, this is the first empirical analysis that reveals how the strength of political favoritism in a distributive policy, such as public disaster relief, varies systematically with the severity of the respective situation.

Based on a simple theoretical model, we argue that biased behavior is not politically affordable and thus not prevalent if a disaster is either very weak or very strong: the allocation of disaster relief is unambiguously required in the former case and clearly unwarranted in the latter. Acting against the public opinion in such situations could be politically costly. However, in the case of medium-strength disasters, when public opinion on whether to provide aid is divided, political influence is substantially larger. These are the situations in which political actors are in a relatively better position to (mis-)use their discretionary power. We show that average estimates do therefore not reveal the full extent of

¹In addition, evidence exists that governments favor areas with electorally more important constituents in their funding allocations (e.g., Kauder et al., 2016; Kriner & Reeves, 2015). Similarly, manifold evidence documents political biases and the existence of political budget cycles in the domain of foreign aid (e.g., Bommer et al., 2019; Dreher et al., 2019; Faye & Niehaus, 2012) and the Bretton Woods institutions (e.g., Eichenauer et al., 2020; Lang & Presbitero, 2018). Kuziemko & Werker (2006) and Dreher et al. (2009) show, for instance, that states with a temporary seat on the U.N. Security Council receive more U.S. aid and a higher number of World Bank projects, respectively. Gassebner & Gnutzmann-Mkrtychyan (2018) find that countries voting in line with the United States are more likely to be given trade preferences.

the alignment bias. It is crucial to account for the nonlinear nature of such relationships, which vary depending on the situational context.

To test these propositions, we present an empirical assessment of all hurricane-related federal disaster declarations between 1965–2018. We analyze presidential declarations in response to random shocks from hurricanes, whose intensities we model by using fine-grid meteorological data. For every hurricane that hit the United States in our 54-year sample period, we apply a meteorological model to estimate the individual spatial destructiveness. This allows us to estimate the political bias for different disaster intensities. Focusing the analysis on U.S. hurricanes has both high socioeconomic relevance and several empirical advantages.

First, hurricanes are the most destructive natural disasters in the United States, with high economic relevance and substantial public attention. Within the last decade, hurricanes have been responsible for more than 50% of all disaster-related damage. The 2017 hurricane season has been the costliest in the United States to date: the three major hurricanes, Harvey, Irma, and Maria, alone caused 3,167 fatalities and USD 278 billion in damage.² The disaster impact literature demonstrates that efficient relief, prevention, and insurance are important to mitigate catastrophic damage from natural disasters (e.g., Davlasheridze et al., 2017; Eichenauer et al., 2020; Healy & Malhotra, 2009; Klomp, 2016).

Second, the random trajectories and varying physical strengths of hurricanes at different locations make them an ideal object of research in our county-level analysis. Given different baseline risks between counties, for which we control by including county fixed effects and county-specific time trends, the timing, location, and severity of hurricane strikes are random and unpredictable (e.g., Aguado & Burt, 2015; Hsiang, 2010; Strobl, 2011).

Third, by combining new data on all causes of hurricane damage (wind speed, rainfall, and storm surge) with our political-economic framework, we are able to present novel causal evidence on whether the U.S. disaster relief system provides assistance to the regions most strongly affected or whether efficient allocation is actually undermined by political factors. The innovation of our approach is that we can measure the pattern of political influence with respect to disaster intensity and thereby identify the situations that are prone to biased decision-making. Our data allow us to flexibly estimate heterogeneous political effects for different levels of disaster intensity. By interacting our political variable of interest with high-dimensional polynomial and semi-parametric hurricane intensity measures, we can test our hypothesis of a nonlinear political bias without making any strict functional form assumptions about hurricane damage or the unknown pattern of political influence.

²Sources for all cited numbers in this paragraph: <https://www.ncdc.noaa.gov/billions/>, last accessed August 6, 2020.

To isolate the political effect, we focus on the president's binary choice to declare an event a disaster or not. Disaster declaration decisions are a unilateral power of the U.S. president (Gasper & Reeves, 2011). A federal disaster declaration is the requirement for relief provision by the Federal Emergency Management Agency (FEMA) and can be requested by state governors. The president does not decide the actual relief payment amounts, which are determined by FEMA bureaucrats during the recovery phase in the years to follow.³

Consequently, we observe a quasi-experiment in which politicians are randomly selected by a stochastic natural process to react to a shock unpredictable in timing and location. Hurricanes trigger the political decision-making process. Since the hurricane season usually ends before major elections take place in November, political factors are predetermined when the disaster strikes; for example, the governor of an affected state, who requests federal relief from the president, is either politically aligned or unaligned with the president. Based on the observed disaster intensity, the president must make a decision as to whether a federal disaster declaration is necessary. To capture the causal political alignment effect, our estimations condition on location, year, time trends, and random hurricane intensity. Our identifying assumption is that there exists no other factor that systematically explains both the political alignment status and the probability of a county to receive a disaster declaration.⁴

Our results show that the probability of receiving a disaster declaration is significantly higher on average when the requesting governor and the president are co-partisans. However, the 2.7-percentage point increase we find on average for all storm intensities conceals the actual heterogeneity of the effect and underestimates its economic significance. Our flexible nonlinear estimations show that political factors are up to eight times more important for medium-strength disasters. The probability of observing a disaster declaration in an area with medium damage increases by up to 21 percentage points for the same disaster intensity if the governor and the president are from the same party. For low and extremely high wind speeds, the influence of political alignment is close to zero and insignificant. Taking the heterogeneous relationship into account, we calculate that the political alignment effect for hurricane-

³For details about the relief system, see Section 2.1 and Appendix A. Data on the actual relief amounts paid out by FEMA for hurricane disasters are only available for a limited period starting in 1998. Similarly, we collected data on governors' declaration requests via a Freedom of Information Act inquiry from FEMA. However, the available time period is only 1992–2018. We show estimations using these data in the appendix. Both analyses yield insignificant results but we do not see them as conclusive due to stark data limitations. We thus focus the analysis on the actual declarations, as the observable outcomes of the declaration process, to assess the degree of political bias in disaster relief allocations. Regions affected by disasters also experience an influx of transfers other than disaster declaration funds. However, the influence of politics cannot be isolated when examining general social welfare payments, disaster loans, private donations or efforts by other non-profit organizations. These all play an important role in disaster response.

⁴To address remaining endogeneity concerns about the alignment status, we show that our results hold in subsamples of close election outcomes, where it is essentially random whether the incumbent governor is aligned or unaligned with the president.

related disasters amounts to at least USD 500 million on average per year. Using conventional average estimates from the related literature would underestimate the economic magnitude by a factor 3 to 5.

We document that other political factors are also most influential for intermediate storm intensities and show further heterogeneities of the analyzed relationship. For instance, our results indicate that areas with low electoral support for the president's party receive fewer declarations and that the alignment effect is more pronounced for governors who have been elected with smaller margins. We do not find differences for the alignment bias between Democrats and Republicans. Using triple interactions, we analyze within- and between-year political relief cycles. We find that presidents are more likely to declare a disaster for storms occurring closer to elections in November.

To document that the results are not driven by particular regions and storm events, we show estimations using separate disaster intensity functions for each state and various subsamples (excluding, for instance, individual decades or states, observations with high leverage and outliers, and focusing on swing states and coastal counties). We also employ a randomization approach based on simulations with placebo treatment allocations to provide additional robust inference for the hump-shaped alignment bias. Not relying on any parametric clustering assumptions, we can infer a positive relationship between political alignment and declarations for a broad range of intermediate wind intensities.

Our findings add to several strands of the literature. First, we contribute to the literature on the alignment bias in intergovernmental transfers. Various studies document this effect for different countries (e.g., [Brollo & Nannicini, 2012](#), for Brazil; [Quinckhardt, 2019](#), for Germany; [Arulampalam et al., 2009](#), for India; [Bracco et al., 2015](#), for Italy; [Fiva & Halse, 2016](#), for Norway; [Curto-Grau et al., 2018](#), for Spain; [Larcinese et al., 2006](#), for the U.S.). While this literature establishes that alignment with the central government is an important political factor to understand biases in distributive politics on average, it remains unclear how this relationship varies in different situations and whether the described linear relationships in the literature are conclusive ([Lang & Presbitero, 2018](#)). Our analysis provides the first systematic test for a nonlinear political bias. We show that specific constellations shape politicians' incentives so that some allocation decisions are prone to an alignment bias, while others are not.

Second, our results correspond to the notion that politicians rather find it feasible to act in a politically biased way when the electorate does not clearly expect a particular action. In that sense, we relate to the debate on whether and when politicians are effectively held accountable for their actions by the electorate (e.g., [Balles et al., 2020](#); [Besley & Burgess, 2002](#); [Besley & Case, 1995](#); [Christenson & Kriner, 2019](#); [Snyder & Strömberg, 2010](#)). Focusing on the importance of media attention, [Durante & Zhuravskaya \(2018\)](#) and [Djourelouva & Durante \(2020\)](#) demonstrate how politicians time unpopular

executive and military actions to days when public attention in the United States is diverted by other events. The novel approach of our analysis is that we do not refer to unrelated third events that divert public attention but that the treatment heterogeneity of the disaster itself creates a variety of situations that are more or less suitable for strategic political behavior.

Third, in studying executive decision-making in the United States, we add to the literature on U.S. distributive politics. Existing studies find, for instance, that states with a higher vote share for the president in previous elections (Dynes & Huber, 2015; Larcinese et al., 2006), areas electing the president's co-partisan House members (Berry et al., 2010; Kriner & Reeves, 2015), and those with Congress members who belong to the majority party (Albouy, 2013) receive more spending. Recent evidence from Bostashvili & Ujhelyi (2019) documents the existence of political budget cycles in U.S. highway spending.⁵ Previous studies on U.S. disaster declarations suggest that election-year cycles exist and that electorally more important or competitive states are favored in the allocation of disaster relief; however evidence on the existence of an alignment bias is mixed (see Garrett & Sobel, 2003; Gasper, 2015; Reeves, 2011). Our new data allow us to provide a more precise analysis. While previous studies cover 8 to 25 years, our county-level panel spans 54 years (1965–2018). Importantly, our approach models disaster intensity directly from fine-grid physical data instead of relying on potentially endogenous reported damage estimates (e.g., the frequently used SHELDUS or EM-DAT data). As our damage data are not self-reported or based on insurance claims and governmental reports, they do not suffer from measurement bias. Furthermore, we include the complete range of hurricane intensities, which avoids arbitrary truncation at certain monetary thresholds.⁶

Fourth, by applying the physical hurricane damage model, our contribution applies recent insights from the disaster impact literature in a political-economic framework. We thereby relate to studies on the effects of extreme weather events (e.g., Auffhammer, 2018; Bakkensen et al., 2018; Elliott et al., 2019; Kalkuhl & Wenz, 2020; Noy, 2009). This literature establishes the analysis of exogenous random weather shocks, such as hurricanes, in economics and studies their manifold socioeconomic consequences (Dell et al., 2012; Deryugina, 2017; Deryugina et al., 2018; Elliott et al., 2015; Felbermayr & Gröschl, 2014; Hsiang & Jina, 2014; Klomp, 2016; Kunze, forthcoming; Strobl, 2011; 2012). We expand the damage literature by using the entirety of physical hurricane damage sources – wind speed, rainfall,

⁵Further evidence on political budget cycles mostly exists for developing countries and young democracies (Aidt et al., 2019; Brender & Drazen, 2008; Gonschorek et al., 2018; Shi & Svensson, 2006). Cole et al. (2012) and Besley & Burgess (2002) find, for instance, that Indian governments increase calamity relief and public food distribution in election years. However, Potrafke (2020) and Schneider (2010) find election-year shifts in budget composition toward more visible government expenditures in established democracies, Bjørnskov & Voigt (2020) show electoral cycles in state of emergency declarations after terrorist attacks, and Bohn & Sturm (2020) present evidence for dampening effects of expected economic downturns.

⁶Appendix D summarizes the criticism regarding the usage of reported damage data (see also Dell et al., 2014; Felbermayr & Gröschl, 2014; Gallagher, 2019). Section 3.1 explains how we overcome these issues by applying physical and meteorological data to proxy for hurricane damage directly, which allows for the exogenous identification of impacts on a fine-grid level.

and storm surge. Overall, spatial wind speed intensities remain the most important physical explanatory variable in our model since storm surge is only present at the coast and precipitation is highly localized. However, controlling for damage in a comprehensive way is useful to isolate political influence from objective factors of need for the issuance of a disaster declaration.

The paper is structured as follows: after motivating our study by presenting a simple theoretical framework for the political economy of disaster relief allocation and deriving our main hypothesis, Section 3 describes our data; we explain the storm intensity measures and how we use them to model disaster severity. Subsequently, we outline our empirical strategy in Section 4. Section 5 contains the results from the empirical estimations and provides various sensitivity tests. The paper concludes with a discussion of the implications of our findings regarding the functioning of democratic control of politicians in general and specific potential changes to the relief system that we propose.

2 Disaster Relief Allocation: A Political-Economic Framework

In this section, we describe the disaster declaration process and introduce a simple model for the president's rationale in allocating disaster relief, which we use to derive our main hypothesis of a heterogeneous political alignment bias. It relates to theoretical models on the political economy of fiscal federalism that account for interactions of different levels of government (e.g., [Bracco et al., 2015](#); [Curto-Grau et al., 2018](#); [Dixit & Londregan, 1998](#); [Geys & Vermeir, 2014](#)). Our model is mainly based on [Arulampalam et al. \(2009\)](#) and [Solé-Ollé & Sorribas-Navarro \(2008\)](#) who assert that the central government can behave opportunistically by using its discretion in grant allocation to make politically motivated transfers to local governments. We adapt the structure of these models to the U.S. disaster declaration framework. Our model introduces the impact of natural disasters and the allocation of disaster relief.⁷ Before presenting the model set-up, the following section briefly explains the system of federal disaster declarations in the United States (see also [Appendix A](#) for an in-depth discussion).

⁷The purpose of our model is to generate insights for the empirical framework of U.S. disaster declarations. However, the model could be developed further to be applicable to other types of aid or salient distributive policies that concentrate benefits in certain regions while being financed through general taxes. This applies, for instance, to international development aid, redistribution schemes intended to support economically weaker regions, or funds allocated according to eligibility criteria, e.g., in the EU (see, e.g., [Asatryan & Havlik, 2020](#); [Budjan & Fuchs, forthcoming](#); [Gehring & Schneider, 2018](#); [Michaelowa et al., 2018](#)).

2.1 Disaster Declarations in the United States

The U.S. president has the executive power to declare a federal disaster, which results in the allocation of public relief funds. The declaration process has been in place since 1950 and has “changed very little over time” (Lindsay & McCarthy, 2015, p. 20). It works as follows: if a natural disaster appears to overwhelm local and state capacities in an affected area, the state’s governor can initiate a preliminary damage assessment and send an official disaster declaration request to the president.⁸ Based on the information collected from the state, FEMA makes a recommendation to the White House, but it is solely at the president’s discretion whether to declare the event a federal disaster (see, e.g., FEMA, 2017). Presidents have wide discretionary power regarding under which circumstances and in which areas they declare a disaster and which requests they deny. Their decision does not require any explanation or justification (Reeves, 2011). The president issues a declaration to a specific state and explicitly lists the counties eligible for federal help.⁹ Only contingent upon a presidential disaster declaration can FEMA then initiate its work on site.

There exist two types of disaster declarations: emergency declarations, which are financially capped and intended to ensure a quick response, and major disaster declarations, which are more comprehensive and essentially release a potentially unlimited amount of money once they are issued. Disaster declarations can cover both public and individual assistance, under which individuals may, for instance, receive financial grants, temporary housing, unemployment benefits, or crisis counseling (see also Appendix A). Crucially, FEMA determines the amount of financial assistance needed and decides which individuals or public entities in the declared area are eligible for relief.

The model that we present in the following section takes the interactions of the different levels of government into account and formalizes the unilateral decision-making of the president as well as the reaction of the electorate.

⁸To facilitate reading, we use the term “governor.” However, tribal chief executives, the mayor of Washington D.C., and the heads of U.S. trust or commonwealth territories, have the same rights to request declarations.

⁹While the governor can propose counties for the disaster declaration, “the president [...] may choose to include some but not all of the counties recommended by the governor” (Sylves, 2008, pp. 83–84). Notably, the president can even declare an emergency without a gubernatorial request when “he determines that an emergency exists for which the primary responsibility for response rests with the United States [...]” (McCarthy, 2014, p. 9).

2.2 A Model of Presidential Disaster Declarations

2.2.1 Model Set-Up and Theoretical Embedding

We study presidential disaster declarations in a two-party system where local governments can be aligned (A) or unaligned (U) with the federal government. Our model incorporates voters' electoral reactions to declarations. As disaster relief is non-programmatic and connected to individual past events, we focus on retrospective voting.¹⁰ We show that the declaration behavior of vote-maximizing presidents differs with the alignment status of the affected counties.

In our model, hurricanes with intensities $s_j \in [0, +\infty)$ randomly hit counties $j = \{1, \dots, N\}$. The corresponding damage $b(s_j) > 0$ is strictly increasing in s_j . U.S. presidents have the power to issue federal disaster declarations $D_j \in \{0, 1\}$ at the county level. Relief amounts $\psi b(s_j)$ for each declaration are determined by FEMA, where $\psi \in (0, 1)$ is the fixed share of damage mitigated due to disaster relief.

Disaster declarations are highly visible. They are usually accompanied by substantive public attention and media coverage, providing information to voters and thereby directing public interest to disaster relief.¹¹ The fact that decisions regarding the issuance of disaster declarations are straightforward to understand and directly observable by the voters distinguishes our study from related models in the literature where voters can only rate the indirect consequences of allocations or politicians' efforts (e.g., Arulampalam et al., 2009; Bracco et al., 2015; Geys & Vermeir, 2014; Hodler et al., 2010).

For simplicity, we assume that voters' electoral decisions are defined by only two criteria. First, a fixed ideological position X_i , which represents the ensemble of all other political preferences as a point in a one-dimensional spectrum (cf. Dixit & Londregan, 1998; Solé-Ollé & Sorribas-Navarro, 2008). The county-specific distribution function $\Phi_j(X_i)$ captures the ideology spectrum of the continuum of voters i in county j , with total population masses normalized to 1. For convenience, we assume a uniform distribution of voter ideologies with $X_i \in [-\frac{1}{2}\omega; \frac{1}{2}\omega]$.¹² More negative values of X_i denote a stronger ideological bias of voters toward the party of the president.

¹⁰Regarding social transfers in general, voters react to both past spending (e.g., De La O, 2013; Levitt & Snyder, 1997; Mancorda et al., 2011) and future promises (Elinder et al., 2015).

¹¹The media plays an important role as an intermediary in disaster assistance by communicating information to the electorate. Eisensee & Strömberg (2007) show that the amount of U.S. aid in response to a foreign disaster was higher over the 1968–2002 period if the disaster received more media attention. Strömberg (2004) finds that U.S. counties with many radio listeners received more relief funds in New Deal spending, and Besley & Burgess (2002) show that Indian governments spend more on relief in the case of food shortages in regions where newspaper circulation is higher. While the focus of our study is not on the role of the media, we can extend our theory to capture the consequences of different levels of national public attention (see Appendix B).

¹²Assuming a uniform distribution on a sufficiently wide ideology interval facilitates the derivation of the alignment bias. Appendix B discusses how different single-peaked voter distributions and densities – representing different levels of electoral competitiveness – affect the strength of the alignment bias.

Second, the voters' electoral decisions depend on the effect of federal disaster relief on their utility u_i . Various studies find that voters blame the government and punish incumbents if a natural disaster occurs (e.g., Cole et al., 2012). However, Gasper & Reeves (2011) show empirically that the electorate behaves "attentively" and rewards politicians in elections for a vigorous disaster response, including federal disaster relief spending.¹³ We incorporate these reactions by integrating disaster damage and relief in the voters' private utility functions u_i with $u'_i > 0$ and $u''_i < 0$:

$$u_i \left(-b(s_j) \cdot (1 - D_j \cdot \psi) - \tau \right). \quad (1)$$

Hurricane damage $b(s_j)$ decreases voters' utility. However, receiving a disaster declaration D_j mitigates hurricane damage by the factor ψ . Therefore, voters' private utility gain from a declaration in their county is strictly positive and increasing in disaster intensity s_j . Relief is funded by lump-sum taxes $\tau = N^{-1} \sum_{l=1}^N (D_l \cdot \psi b(s_l))$.¹⁴ Taking the utility functions u_i and the ideological positions X_i into account, voter i decides to vote for the president's party if

$$u_i \geq X_i. \quad (2)$$

In general, however, presidential disaster declarations are preceded by a governor's request. We assume that voters also account for the local governor's efforts and attribute some share of the utility gain from disaster relief to the governor's party. That is, if the governor is politically unaligned with the president, the president's party might capture less of the voters' reward for a declaration, even in a federal election (cf. Curto-Grau et al., 2018; Geys & Vermeir, 2014). Therefore, we define $\theta \in [0, 0.5]$ as the amount of "vote leakage" (Arulampalam et al., 2009; Solé-Ollé & Sorribas-Navarro, 2008), i.e., the share of voter goodwill that the president's party does not receive.¹⁵ In unaligned counties, the electorate's support for the president's party is then defined as

$$(1 - \theta)u_i \geq X_i + \theta u_i. \quad (3)$$

¹³See also the evidence presented by Bechtel & Hainmueller (2011) for Germany, Cole et al. (2012) for India, Lazarev et al. (2014) for Russia, and Gasper & Reeves (2011) as well as Healy & Malhotra (2009) for the United States. A recent reanalysis of Gasper & Reeves (2011) by Gallagher (2019) finds no evidence for attentive behavior of the electorate after applying corrections to the data used (see also our discussion about reported damage data in Appendix D).

¹⁴A declaration in another county ($l \neq j$) affects voters' utility indirectly as they face higher taxes. However, we can also incorporate the electorate's opinions on other declarations directly by adding a component to the model that captures voters' social and fairness concerns about declarations in other counties. Appendix B explains how a higher importance of fairness considerations and the strength of the national public opinion can decrease the extent of the alignment bias.

¹⁵We focus the analysis on presidents, who have the declaration decisions in all counties at their disposal. As we assume that local governors only care about the utility of their own constituents, they always have an incentive to request disaster relief (cf. Carozzi & Repetto, 2016; Weingast et al., 1981). We restrict the analysis to the case where $\theta \in [0, 0.5]$. Values > 0.5 (i.e., the governor's party capturing more benefits from a presidential declaration than the presidents themselves) would imply reversed incentives for the president as the marginal utility of declarations becomes negative in unaligned counties (Solé-Ollé & Sorribas-Navarro, 2008).

If the state government and the president happen to be aligned, there is no “vote leakage” to the opposition party ($\theta = 0$). The expression simplifies to Equation (2), and the president’s party captures the entire electoral benefit from a declaration.

In practice, $\theta > 0$ represents the conflicting incentives that presidents face when declaring a disaster in an unaligned county. Neither governors nor presidents can be assumed to willingly offer a stage for the opposing party to claim the benefits of disaster relief, but they would also want to benefit from the electoral reward of a declaration themselves. In the aligned case ($\theta = 0$), incentives to support co-partisans are manifold as politicians need them to follow through with their political agenda or to defend their political legacy (Alesina & Tabellini, 2007). Particularly for upcoming election campaigns, where key aligned politicians act as major endorsers and campaigners for their parties’ candidates, it is important to strengthen their own political team and alliances (cf. Ansolabehere & Snyder, 2006; Carozzi et al., 2019; Zudenkova, 2011).

In summary, the president faces different voter reaction functions when deciding on disaster declarations for aligned (A) and unaligned (U) counties:

$$\hat{X}_i^A = u_i \geq X_i \quad (4)$$

$$\hat{X}_i^U = (1 - 2\theta)u_i \geq X_i. \quad (5)$$

\hat{X}_i^A and \hat{X}_i^U are the thresholds below which voters vote for the party of the president. By issuing a disaster declaration, the president can shift \hat{X}_i . Thus, the presidents’ decisions can alter the number of votes for their party by making some voters with ideological positions close to the threshold change their vote decision. The degree to which a disaster declaration shifts \hat{X}_i depends on various factors. It will, for instance, take a larger shift to the right if hurricane intensity s is higher and if the respective governor is politically aligned.

2.2.2 Alignment Bias in Disaster Relief Allocation

We assume that presidents maximize the electoral support for their party across all counties using the following objective function:

$$\max_{D_j^A, D_j^U} \sum_{j=1}^{N^A} \Phi_m(\hat{X}_i^A) + \sum_{j=1}^{N^U} \Phi_n(\hat{X}_i^U), \quad (6)$$

where $D_1^A, \dots, D_{N^A}^A$ and $D_1^U, \dots, D_{N^U}^U$ are the $N = N^U + N^A$ declaration decisions in all aligned (A) and unaligned (U) counties. The first-order conditions (FOCs) of this optimization are the *ceteris paribus*

differences in electoral support for the president from issuing a declaration in county j . To shorten the notation in this binary optimization, we write the FOCs as $\Delta \Phi_j^A = 0$ and $\Delta \Phi_j^U = 0$, respectively.¹⁶ To isolate the alignment effect, we assume that the distribution function Φ and voter preferences u_i are equal in aligned and unaligned counties.

Due to the concavity of the utility function, presidents receive a higher electoral reward for declaring a disaster in more severely affected areas (i.e., when $b(s_j)$ is high). Based on the FOC's, they decide to declare a disaster in all counties above a certain hurricane intensity threshold s^* . *Ceteris paribus*, this critical threshold s^* , however, differs between aligned (A) and unaligned (U) counties. Due to vote leakage (θ), presidents receive a higher reward for issuing a declaration for the same hurricane intensity in aligned counties compared to unaligned counties. Therefore, $s^{*U} > s^{*A}$ is required so that $\Delta \Phi^A = \Delta \Phi^U = 0$ holds with any share of vote leakage $0 < \theta < 0.5$. Hence, the critical hurricane strength above which it is optimal for the president to issue a disaster declaration is higher for unaligned counties than for aligned counties.

$$D_j^* = \begin{cases} 1 & \text{if } s_j > s^{*U} \\ 1 & \text{if } s^{*U} \geq s_j > s^{*A} \wedge \theta = 0 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

For hurricanes with very high [very low] intensities, all impacted counties receive [do not receive] a declaration irrespective of their alignment status. The alignment bias effectively affects only counties that fall within an intermediate interval of disaster severity. In these cases, the president only declares a disaster if a county is aligned. The alignment bias affects counties in a wider *Wind Speed* interval – that is, the difference between s^{*U} and s^{*A} is greater – when the amount of vote leakage θ is higher. More electoral reward leaking to the opposite party, reduces the political incentives for presidents to declare a disaster for a given hurricane intensity. Furthermore, we discuss in Appendix B how the influence of several extensions such as different distributions of voter ideology, the existence of fairness considerations and differences in the national public opinion shape the president's declaration incentives.

Beyond the emergence of an average alignment bias, we derive the crucial refinement that certain constellations influence the incentives of election-motivated politicians such that some allocation decisions are susceptible to an alignment bias while others are not. This theoretical result corresponds to

¹⁶ $\Delta \Phi_j^A = \omega^{-1} \left(u_i(D_j = 1, s_j) - u_i(D_j = 0, s_j) + \sum_{l=1, l \neq j}^N (1 - 2\theta_l) (u_l(D_j = 1, s_j) - u_l(D_j = 0, s_j)) \right) = 0$ and $\Delta \Phi_j^U = \omega^{-1} \left((1 - 2\theta) (u_i(D_j = 1, s_j) - u_i(D_j = 0, s_j)) + \sum_{l=1, l \neq j}^N (1 - 2\theta_l) (u_l(D_j = 1, s_j) - u_l(D_j = 0, s_j)) \right) = 0$. It follows from the concavity of the utility function that $\Delta \Phi_j > 0$ if s_j is large enough. This rules out a corner solution with no declarations in unaligned counties. See also Appendix B for a discussion of potential corner solutions of the model.

our hypothesis that political considerations in relief allocation only come into play for medium-strength disasters, i.e., when public opinion is not entirely for or against issuing a declaration. These are the situations in which politicians can make use of their discretion to pursue their strategic political goals. We test our theoretical result of a heterogeneous political bias in our empirical analysis.

3 Data

3.1 Hurricane Data

Hurricanes are chaotic weather shocks that hit the United States in a season usually ranging from June to November each year.¹⁷ Even 48 hours before landfall, the exact hurricane location is impossible to predict (Aguado & Burt, 2015; Rappaport et al., 2009), which is reflected in the chaotic behavior of hurricane raw tracks displayed in Panel [a] of Figure 1. In general, hurricanes have three major damage sources: wind, excessive rainfall, and storm surge along the coast. As wind intensity is highly correlated with the other two damage sources, the literature commonly uses wind speed as the sole damage proxy (Hsiang, 2010; Kunze, forthcoming; Strobl, 2011). We additionally model damage using new rainfall and coastal flooding data to account for all possible sources of hurricane damage. However, as rainfall is highly localized and storm surge occurs only in coastal counties, we utilize wind intensity as our primary damage variable while always controlling for the other two factors.

To model hurricane damage, we use meteorological data on wind speed for the years 1965–2018 from the IBTrACS data set (Knapp et al., 2010) provided by the National Oceanic and Atmospheric Administration (NOAA). It contains data on all hurricanes, tropical storms, and tropical depressions collected from various weather agencies via satellites, ships, airplanes, or weather stations. The raw tracks data include six-hourly observations of the exact position, wind speed, and minimum sea pressure of each storm. However, the raw data tracks, as displayed in Panel [a] of Figure 1, have no information on the spatial size and destructiveness of hurricanes. To calculate spatial destructiveness, we apply the implementation of the meteorological *CLIMADA* model (Aznar-Siguan & Bresch, 2019) by Kunze (forthcoming), which generates spatially varying wind fields for each individual storm track in the sample at a resolution of 1×1 km. Appendix E describes the wind field model in more detail. In total, we have data on 275 tropical cyclones in our sample. Panel [b] of Figure 1 displays the average wind speed exposure over the 1965–2018 period, as derived from our wind field model.

¹⁷See Appendix C for details about hurricane genesis and impacts.

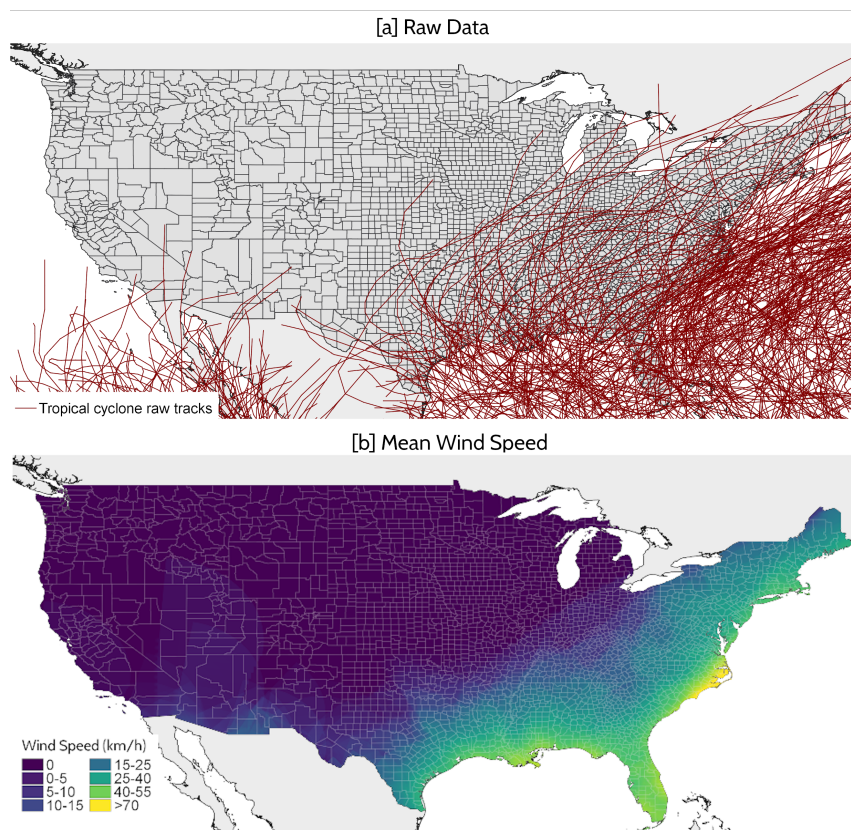


Figure 1: **Hurricane Raw Tracks and Modeled *Wind Speed* Average, 1965–2018**

Panel [a] displays the tropical cyclone raw tracks (red lines). Panel [b] shows the average annual *Wind Speed* exposure for the period 1965–2018 computed from our meteorological wind field model. The different colors represent average *Wind Speed* intensities, ranging from purple (0 km/h) to yellow (>70 km/h).

The variable *Wind Speed* represents the maximum annual hurricane-related wind speed in each county. We thereby account for the most damaging hurricanes per county and year, which are responsible for the majority of catastrophic consequences and are established as a valid predictor of destruction and disaster declarations (Hsiang, 2010; Murnane & Elsner, 2012; Nordhaus, 2010; Strobl, 2011). Appendix Figure K1 shows the strong relationship between *Wind Speed* and the likelihood of observing a disaster declaration. The majority of the affected counties (66%) have one hurricane event per year. Around 22% have two events per year. To account for the possibility of multiple shocks, we include the yearly frequency of hurricanes in a robustness test. Since the hurricane data are available at a higher time frequency than years, we also generate a variable where we collect the exact month for the strongest hurricane per county-year observation.

In comparison to other political-economic studies, the usage of the physical intensity data is a clear advantage. Older studies (e.g., Davlasheridze et al., 2017; Eisensee & Strömberg, 2007; Gasper, 2015; Healy & Malhotra, 2009; Reeves, 2011) rely primarily on reported damage data, such as SHELDUS or EM-DAT, which are prone to measurement errors, missing data, and endogeneity (see Appendix D;

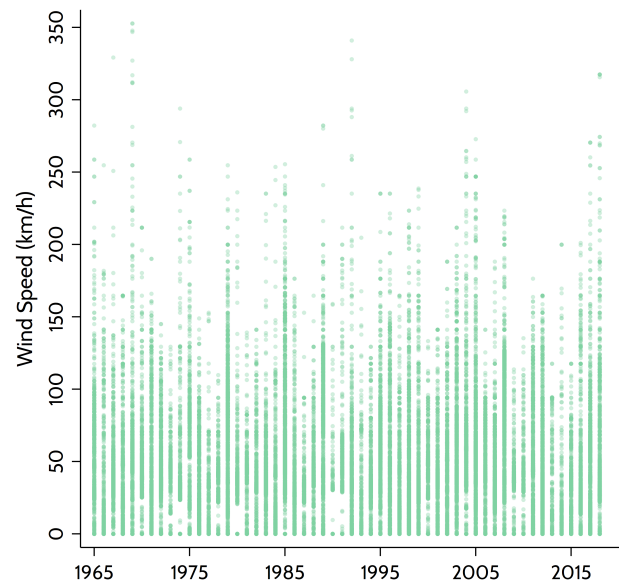


Figure 2: **Yearly Variation of Maximum *Wind Speed* per County, 1965–2018**

Each point in the figure represents one county-level *Wind Speed* observation over the period 1965–2018.

Felbermayr & Gröschl, 2014; Gallagher, 2019; Kousky, 2014). We circumvent these problems by applying objective and exogenous physical intensity measures to model damage from hurricanes.

Figure 2 displays the annual variation of the *Wind Speed* variable at the county level. One can see that the exposure to hurricanes varies significantly over time. Given the nature of the wind field model, observations well below the common hurricane threshold of 119 km/h are present in our data for two reasons. First, the raw data include all tropical cyclones. In addition to hurricanes, the IBTrACS data set also covers less intense tropical storms and tropical depressions. Second, the wind field model computes wind intensities for the whole size of the hurricane. Typically, the most intense wind speeds occur around the eyewall, at the center of the hurricane, while wind speeds decrease when moving further away from the center. To show the robustness of our approach, we also calculate specifications without less intense tropical cyclones and with a specific hurricane damage function proposed by Emanuel (2011), which uses a particular functional form with a lower bound cut-off value (see Appendix E).

To also account for the two remaining damage sources of hurricanes, namely, storm surge and rainfall, we control for their influence in all our specifications. We use the newly developed storm surge data set by Kunze & Strobl (2020) to generate the maximum inundation level (*Storm Surge*, in meters) per county and year. The data is based on a hydrodynamic model that generates one-hourly water level maps at the coast for all tropical cyclones recorded in the IBTrACS data set (Knapp et al., 2010). In addition, we also control for hurricane-related *Rainfall*, which is another cause of hurricane damage (Bakkensen et al., 2018). Unlike wind speed, precipitation does not decrease steadily when moving away from the storm's center. Our variable captures the maximum total rainfall (in mm) collected from

weather stations during the occurrence of individual hurricanes in affected counties. We construct the *Rainfall* variable from the raw data of Roth (2018). The special feature of our rainfall data is that they solely capture precipitation from hurricanes at exact coordinates. *Rainfall* thus accounts for the maximum hurricane-related precipitation value per county and year.

3.2 Disaster Declarations

The raw data for our dependent variable *Declaration* originate from the *openFEMA* database (FEMA, 2019a), which contains a county listing of all disaster declarations since 1965. Consequently, our level of analysis is the county-year level. We construct *Declaration* as an indicator taking the value 1, if a county received at least one hurricane-related disaster declaration in a given year, and 0 otherwise. Following Reeves (2011), we include both major disaster declarations and emergency declarations for our indicator.¹⁸ We also present results with a separate indicator for emergency and major disaster declarations. In our data, 8,094 county-year observations received at least one *Declaration*. Furthermore, we collected information on disaster declaration denials by the president via a Freedom of Information request (2019-FEFO-00419) to FEMA. Unfortunately, data on rejected requests for hurricane disasters are limited and cover the 1992–2018 period, with only 142 official county-year declaration denials reported to us by FEMA in connection with tropical cyclones.¹⁹ The variation is too small to infer any robust relationships, but for completeness, we show results where we include data on FEMA requests in the appendix (Table K1).

3.3 Political Variables of Interest

To assess the effect of governors and presidents being fellow party members, we construct the variable *Aligned Governor* based on data from Klarner (2013) and the National Governors Association. It takes the value 1 if the president and the governor belong to the same political party and 0 if otherwise.²⁰ On average, the *Aligned Governor* status changed 10.7 times for an individual county during the 54 years of our sample. Analogously, we construct binary variables for congressional politicians' party affiliations

¹⁸In addition to declarations in the incident type category “Hurricane,” we included declarations from the categories “Coastal Storm,” “Flooding,” and “Severe Storm(s)” if they contain a clear reference to a specific tropical cyclone in their title or can be matched via the date of occurrence to storms in our data set. We exclude the exceptional evacuation for Hurricane Katrina victims where all counties in the nation that hosted evacuees received a declaration despite not being affected by the hurricane. Only 2% of the county observations received more than one declaration per year. Using the number of declarations as a dependent variable might cause problems due to double declarations for individual disasters (see Reeves, 2011). *Declaration* is not prone to these outliers. Nonetheless, we show results using the count variable *Declarations* (total annual number of declarations per county and year) in the appendix.

¹⁹According to FEMA, this data set is complete with no deletions or exemptions.

²⁰The variable indicates the party affiliation at the beginning of November (i.e., at the point of a potential presidential election). In case of independent governors, we code it as 0.

(*Aligned Representative*) and for the two incumbent senators (*Aligned Senators*) being co-partisans of the president.²¹

Additionally, we exploit data on past election outcomes to test further political channels. For instance, we create two indicator variables for high- and low-support districts. The variable *High-Support District* takes a value of 1 if the incumbent president’s party gained more than 60% of the votes in the most recent election and 0 if otherwise. If it won less than 40% in the last election, the variable *Low-Support District* is coded as 1. We also analyze close-election subsamples and how the alignment bias differs with respect to the margin of victory of the respective governors in the previous gubernatorial election.

We document all variables explained above, as well as further covariates and their sources, in Appendix F. Observations in our data cover all counties from the contiguous United States if they have a positive value for *Wind Speed*, *Rainfall*, or *Storm Surge*.²² The final panel data set consists of 85,309 county-year observations over the 1965–2018 period. As a robustness test, we also show results using a fully balanced panel including observations not affected by a hurricane in a specific year, which inflates the data set with zeros (see Figure J5). Table 1 shows descriptive statistics for the main variables used in the analysis.

Table 1: **Summary Statistics of the Main Variables**

	Observations	Mean	St. Dev.	Min	Max
<i>Declaration</i>	85,309	0.08	0.27	0.00	1.00
<i>Emergency Declaration</i>	85,309	0.03	0.18	0.00	1.00
<i>Major Declaration</i>	85,309	0.06	0.24	0.00	1.00
<i>Declarations</i>	85,309	0.11	0.41	0.00	5.00
<i>Aligned Governor</i>	85,309	0.46	0.50	0.00	1.00
<i>Aligned Representative</i>	85,309	0.47	0.50	0.00	1.00
<i>Aligned Senators</i>	85,309	0.30	0.46	0.00	1.00
<i>Alignment Count</i>	85,309	1.94	1.25	0.00	4.00
<i>Wind Speed</i>	85,309	24.28	37.37	0.00	352.71
<i>Rainfall</i>	85,309	57.77	67.63	0.00	1,538.73
<i>Storm Surge</i>	85,309	0.04	0.27	0.00	6.01
<i>Hurricane Month</i>	84,947	8.38	1.35	5.00	11.00

See Appendix Table F1 for the full summary statistics.

²¹We further construct the variable *Party Alignment*, which counts how many of the aforementioned political actors are aligned with the president’s party. We use election data to generate variables for party affiliations of incumbent House members. The data were provided by James M. Snyder. Previous versions of this data set are used in Hainmueller et al. (2015) and Eggers et al. (2015). To match voting district data from the House to individual counties, we apply a population weighting procedure. To code *Aligned Senators*, we use state-level election results from the CQ Voting and Elections Collection.

²²We exclude Hawaii, Alaska, Washington D.C., and all U.S. overseas territories from the analysis due to their locations, lack of data availability or quality in the observation period, and their different political and electoral rights.

4 Empirical Strategy

We analyze presidential disaster declaration decisions after hurricanes hitting the United States. As Section 2.1 explains, presidents have the discretion to declare an event a disaster or not. We use a setting that allows us to identify systematic political biases in the declaration allocations.

Previous studies document political influence in distributive politics. However, analyses of government spending often deal with various sources of endogeneity and uncertainty about the channels of the effect. What is often unclear is whether the observed favoritism is due to the politicians' direct actions or engagements in different forms of log-rolling. Usually, executive politicians can also control the timing of their decisions to a certain extent as part of an endogenous process. Political alignment biases sometimes have a mechanical explanation in that an incumbent's ideology is consistent with the spending preferences of the areas from which politicians receive the most electoral support and that are more often politically aligned.

Our strategy overcomes potential endogeneity issues by exploiting the fact that, conditional on location, hurricane incidence and severity are random (e.g., Dell et al., 2014; Deryugina, 2017; Kunze, forthcoming; Strobl, 2012). That is, we observe a quasi-experiment in which politicians are randomly selected by a stochastic natural process to react to a shock unpredictable in timing and location. Hurricanes trigger the political decision-making process (i.e., politicians cannot opt-out or postpone their decision). They are prompted to make a declaration decision given a current exogenous event. At this point in time, all political factors are predetermined; for example, the governor of an area hit by a storm is either aligned or unaligned with the president. An additional property of hurricanes is that the hurricane season ranges from June to November. It therefore typically ends before general elections take place in November, which could alter the alignment status, potentially causing reverse causality problems.

Furthermore, the shock that politicians face is characterized by highly heterogeneous treatment patterns. Hurricanes have different strengths, and, for each individual storm, damage can range from devastating (for areas hit by the eye of a hurricane) to very light (for those affected by outer bands of a storm system). This heterogeneity in the degree to which areas incur damage corresponds to different levels of need for a declaration in each place. As explained in the previous section, we rely on the assumption that stronger hurricanes, *ceteris paribus*, cause more damage.²³

It is evident that our estimation strategy can only work in a fixed effects within-estimation framework. Locations differ in their exposure to hurricanes; for instance, coastal counties in the Southeastern United

²³To also account for the possibility that different levels of wind speed region-specifically correspond to different levels of damage and need for relief between locations (e.g., due to differences in wealth or infrastructure), we show that our results are robust to allowing separate damage proxies for each state in Appendix Figure J9.

States have a higher baseline risk of being affected by a tropical storm. Additionally, some counties might have a more vulnerable infrastructure or population than others. We account for such unobserved heterogeneities that are constant over time by including county fixed effects. Similarly, differences between years (e.g., due to extraordinary storm seasons, different government administrations, national elections, and general technical improvements) cause temporal heterogeneities. These are captured by year fixed effects. Additionally, some structural differences between locations may have changed over the course of our 54-year-long panel. For instance, climatic changes may have altered the baseline pattern of storm occurrence, mitigation efforts may have changed over time, or the vulnerability of the population may have changed. We thus allow for individual linear time trends for each county. Accordingly, the following least-squares equation represents the starting point for our analysis:

$$Declaration_{i,t} = \alpha + \beta Aligned\ Governor_{s,t} + \gamma Wind\ Speed_{i,t} + \mathbf{X}'_{i,t}\mu + \sigma_i + \tau_t + \sigma_i \times T_t + \varepsilon_{i,s,t}, \quad (8)$$

where *Declaration* is the binary indicator for disaster declarations received by county *i* in year *t*.²⁴ Our main variable of interest is the indicator *Aligned Governor*. Additionally, $\mathbf{X}_{i,t}$ represents the vector of further explanatory variables, including other potential hurricane damage sources such as *Rainfall* and *Storm Surge*, and the alignment statuses of the House representatives and senators (*Aligned Representative* and *Aligned Senators*). The equation contains county fixed effects (σ_i), year fixed effects (τ_t), and county-specific linear time trends ($\sigma_i \times T_t$); $\varepsilon_{i,t}$ is the error term. While the inclusion of further covariates might improve efficiency, we do not include socioeconomic controls that are themselves likely outcomes of the exogenous storm shocks (see, e.g., Dell et al., 2014). Nevertheless, we show in Appendix Table G4 and Figure JII that our results do not change significantly when we add a vector of socioeconomic control variables including county-level income, population, and race.

Throughout the analysis, our identifying assumption for the estimation of political influence is that, conditional on the location, year, time trends, and hurricane strength, there exists no other explanatory factor that systematically explains both the political alignment status and the probability of a county to receive a disaster declaration. A remaining concern might be that political alignment is not the result of an exogenous process. To show that our results are not flawed due to any systematic correlations with unobserved factors, we run robustness tests that draw on close election outcomes. In situations where incumbent governors win the election by a very close margin, it is quasi-random whether the state

²⁴We estimate least-squares FE-within regressions using the `reghdfe` command (written by Correia, 2017) in Stata. For robustness, Appendix Table G3 also shows maximum-likelihood estimates from conditional fixed effects logit and probit models. We also run Poisson and Poisson pseudo maximum likelihood (PPML) models using the number of *Declarations* as dependent variable and controlling for the number of hurricane events in a year. Coefficients of *Aligned Governor* are positive and significant in all alternative models. Average partial effects from the logit and probit regressions are nearly the same size as the coefficients in the linear probability model.

they represent is politically aligned or unaligned with the incumbent president because the alignment status changes discontinuously at the 50% threshold (e.g., [Brollo & Nannicini, 2012](#); [Eggers et al., 2015](#); [Pettersson-Lidbom, 2008](#)). We document the robustness of our full-sample findings in subsamples defined by different closeness bandwidths (see Figure 5).

The baseline equation presented above takes a structural approach in modeling storm damage. This strict linear functional form assumption might serve as an acceptable proxy for disaster severity, but abandoning it has major advantages for our study. First, we can show that our results do not depend on any potentially erroneous functional form assumption and that they hold when disaster severity is modelled flexibly. Second, and most importantly, only dropping this static linear assumption allows us to test our main hypothesis of heterogeneous political effects.

To account for nonlinearities in a flexible way, we introduce two approaches. First, we replace the linear *Wind Speed* variable with a *Wind Speed* polynomial ($\sum_{b=1}^4 \gamma_b \text{Wind Speed}_{i,t}^b$). We additionally interact the entire polynomial with our political variable of interest (*Aligned Governor*). The equation then becomes

$$\begin{aligned} \text{Declaration}_{i,t} = & \alpha + \beta \text{Aligned Governor}_{s,t} + \sum_{b=1}^4 \gamma_b \text{Wind Speed}_{i,t}^b \\ & + \sum_{b=1}^4 (\delta_b \text{Wind Speed}_{i,t}^b \times \text{Aligned Governor}_{s,t}) + \mathbf{X}'_{i,t} \mu + \sigma_i + \tau_t + \sigma_i \times T_t + \varepsilon_{i,s,t}. \end{aligned} \quad (9)$$

We aim for a parsimonious baseline model so as to not inflate the regression unnecessarily with additional parameters, which allows us to analyze subsamples or to add further interactions. Based on a sequence of *F*-tests, we select a quartic *Wind Speed* polynomial for our baseline model. Note that our results are robust to including higher order polynomials up to ninth degree (see Appendix J8).²⁵

The second approach is inspired by [Schlenker & Roberts \(2009\)](#) and [Deschênes & Greenstone \(2011\)](#): it models hurricane strength semi-parametrically by defining bins of wind speed $\sum_{j=1}^{10} \gamma_j \text{Wind Class } j_{i,t}$. These are dummy variables that indicate whether the respective observations of *Wind Speed* fall into a certain interval. Analogously to the polynomial approach, all dummy variables are then interacted with the political variable of interest. *Wind Speed* can hence flexibly affect the probability of a disaster

²⁵To select a baseline for the *Wind Speed* polynomial, we run a sequence of *F*-tests for all possible choices in which we compare an unrestricted model including interacted *Wind Speed* polynomials up to degree n with a more restricted nested model with degree $n - 1$. Using both backward and forward selection, we obtain a polynomial of fourth degree. Higher order polynomials do not yield a significantly better fit to explain declarations. Appendix Table H3 shows the respective *F*-statistics. Note that we cannot simply rely on conventional damage functions or simpler functional forms used in the literature as we model the political effect of disaster declarations and not only, e.g., hurricane damage. Additionally, we particularly argue in our theoretical model that the political influence is nonlinear.

declaration and we can estimate a separate marginal effect of the interacted political factor for every wind intensity interval.²⁶

To make use of the fine-grid variation of our hurricane and declaration data, we run disaggregated estimations at the county level. The main variable of interest, *Aligned Governor*, varies on the state level. However, disasters are declared for specific counties within states. The underlying standard error structure cannot be assumed to be independent across counties and years since hurricanes affect neighboring counties in a similar way, and declarations are issued in bundles of counties. Furthermore, a county's history of storms and declarations or its geographic location might induce autocorrelation. To be conservative regarding inference, all our estimations allow error correlation both within and between observations, and we cluster standard errors on the state \times year and county level. Appendix Table G1 and Figure J1 show that our results are robust to all possible conventional choices of clustering the standard errors, which include clustering at the county, county & year, year, state, state \times year, hurricane, and hurricane \times state level. Additionally, the results are also robust to arbitrary spatial HAC-errors (Colella et al., 2019) that allow errors to be correlated within a 1,000 km radius and 10 years.

Furthermore, we calculate a permutation p -value based on a nonparametric inference method applying placebo treatment allocation in the spirit of Chetty et al. (2009). Using this simulation, we can also calculate confidence intervals for the political effect at each wind speed without a parametric clustering assumption. None of the alternative inference methods suggest that we falsely reject the null hypothesis in the broad intermediate range of wind intensities that we show the relationship to be robust for.

5 Results

5.1 Average Alignment Effects

Turning to the results, we first provide estimates for the average relationship of political alignment and disaster declarations. This approach adds to results on the alignment bias from the previous empirical literature while making use of our fine-grid hurricane data. Table 2 shows the estimates from six fixed effects regressions explaining the issuance of disaster declarations. All estimations include county and year fixed effects and use the entirety of the 85,309 county-year observations affected by a hurricane from 1965–2018. Our estimations control for storm intensity directly. In all regressions, coefficients of *Wind Speed* and our additional *Rainfall* control are highly significant, explaining a large share of the

²⁶The *Wind Speed* bins each consist of a 25 km/h interval between 0 and 225 km/h and one additional category representing all wind observations above 225 km/h. Zero-*Wind Speed* observations are the omitted category (observations only treated with positive storm-associated rainfall). The only functional form assumption of this approach is that effects are constant within bins.

Table 2: **Regression Results – Average Estimates**

Dep. Var.: <i>Declaration</i>	(1)	(2)	(3)	(4)	(5)	(6)
<i>Aligned Governor</i>		0.032 (0.012) [0.006]	0.027 (0.011) [0.020]	0.027 (0.011) [0.011]	0.027 (0.011) [0.013]	0.026 (0.011) [0.014]
<i>Aligned Representative</i>			0.012 (0.005) [0.017]	0.010 (0.005) [0.054]	0.010 (0.005) [0.054]	0.010 (0.005) [0.048]
<i>Aligned Senators</i>			0.026 (0.013) [0.045]	0.024 (0.014) [0.091]	0.027 (0.014) [0.060]	0.026 (0.014) [0.066]
<i>Wind Speed (St. Dev.)</i>	0.075 (0.007) [0.000]	0.075 (0.007) [0.000]	0.075 (0.007) [0.000]	0.074 (0.007) [0.000]		
<i>Rainfall (St. Dev.)</i>	0.072 (0.005) [0.000]	0.072 (0.005) [0.000]	0.072 (0.005) [0.000]	0.069 (0.005) [0.000]	0.069 (0.005) [0.000]	0.069 (0.005) [0.000]
<i>Storm Surge (St. Dev.)</i>	0.032 (0.010) [0.001]	0.031 (0.010) [0.001]	0.031 (0.010) [0.001]	0.030 (0.010) [0.002]	-0.002 (0.009) [0.806]	-0.002 (0.009) [0.789]
Time Trends				X	X	X
Wind Speed Polynomials					X	
Wind Speed Bins						X
Observations	85,309	85,309	85,309	85,309	85,309	85,309

The table displays regression coefficients with two-way clustered standard errors on the state × year and county level in parentheses (Appendix Table G1 documents robustness toward alternative clustering choices). *p*-values are in brackets. All estimations use the linear fixed effect-within estimator and include county and year fixed effects (Appendix Table G3 shows the robustness of the results to using alternative estimations such as conditional logit and probit). *Wind Speed*, *Rainfall*, and *Storm Surge* are shown in standard deviation increases (above zero). Standard deviations for *Wind Speed*, *Rainfall*, and *Storm Surge* are 38.78 km/h, 68.17 mm, and 0.8 m, respectively. Models 4–6 include county-specific linear time trends. “Wind Speed Bins” signifies the usage of the semi-parametric approach to model wind speed, and “Wind Speed Polynomials” indicates the usage of quartic polynomials. The sample runs from 1965–2018 in all regressions.

overall variation in disaster declarations.²⁷ Notably, when comparing column 1, which only includes the hurricane measures, with the other specifications in Table 2, neither the coefficient size nor the significance of the hurricane variables is affected by the inclusion of the political variables. A one standard deviation increase (approx. 39 km/h) raises the probability of a disaster declaration by about 7.5 percentage points.

The second column adds our main variable of interest, *Aligned Governor*. The estimated coefficient of 0.032 is highly significant with a *p*-value of 0.006. It signifies that, *ceteris paribus*, counties have, on average, a 3.2 percentage point higher chance of receiving a disaster declaration if the president and the governor are aligned. The coefficient of *Aligned Governor* remains remarkably stable when including other political variables of interest. *Aligned Representatives* and *Aligned Senators* are also related to a higher probability of receiving a disaster declaration (column 3). Unlike governors, representatives and

²⁷*Storm Surge* is significant and positive in the first four columns but shows an insignificant coefficient close to zero once we include the *Wind Speed* polynomial. While *Wind Speed* and *Rainfall* explain the variation of *Declaration* in all counties, *Storm Surge* is only an important factor in low-elevation coastal zones (see Section 3.1 and Kunze & Strobl, 2020). In addition, it is highly correlated with higher orders of *Wind Speed*. We still include *Storm Surge* in all our regressions to capture all potential damage sources of hurricanes directly.

senators are not directly involved in the process of requesting declarations. However, they can also lobby the president, for example, by writing supporting letters for governors' requests.²⁸ Significance for the senators is lower than for the representatives. The latter represent smaller areas, making it more likely that their entire electoral district is affected.

In the fourth column of Table 2, we allow for the existence of county-specific time trends, which account for any structural changes affecting the baseline probability of a county receiving federal disaster relief. While the coefficient of our main variable of interest, *Aligned Governor*, stays at the same level and even increases its *p*-value (0.011), the estimates for the representatives and senators are somewhat weaker.

Although these first results support the evidence for an alignment bias “on average” that other studies have documented, we rate these average estimates as insufficient to uncover the true pattern of political influence. The previous approach treats all situations as equal in terms of potential exertion of political influence. However, as our theory section (2.2) outlines, we hypothesize that the strength of political effects is very heterogeneous and highly dependent on the situation politicians are faced with. Attempts to capture the alignment effect with a single parameter thus involve overly stark assumptions and simplifications. To solve this issue, we introduce two flexible approaches that do not impose a strict functional form assumption. This then allows us to determine individual alignment effects for each storm intensity.

Columns 5 and 6 form the basis for our flexible estimations. By including a quartic *Wind Speed* polynomial and 10 separate 25 km/h wind speed bins, respectively, the marginal effect of hurricane strength varies for different levels of *Wind Speed*. While the average political effects remain still unchanged in these estimations, we interact our political variable of interest with the flexible hurricane measures to obtain separate estimates of political influence for the different storm intensities in the following section.²⁹

5.2 Main Results: Heterogeneous Alignment Bias

Our fine-grid storm data allow us to drop the static assumption of a homogeneous political alignment bias. By interacting *Aligned Governor* with all factors of the *Wind Speed* polynomial (in the polynomial

²⁸As Sylves (2008, p. 91) explains, “researchers have discovered in presidential library documents evidence that presidents considering a disaster declaration [...] receive, as a matter of routine, a list of the names of the lawmakers whose districts are affected by a disaster event.”

²⁹To show the robustness of the average effects, we run several specifications. Appendix Table G2 includes a variable for past *Declaration* and past *Wind Speed*. Table G3 demonstrates that our results are robust to different regression model choices (logit, probit, Poisson, Poisson pseudo-maximum likelihood). Finally, our findings still hold when we include a set of lagged socioeconomic control variables covering logs of *Population*, *Black Population*, *Real Income*, and *Per Capita Real Income* (see Table G4).

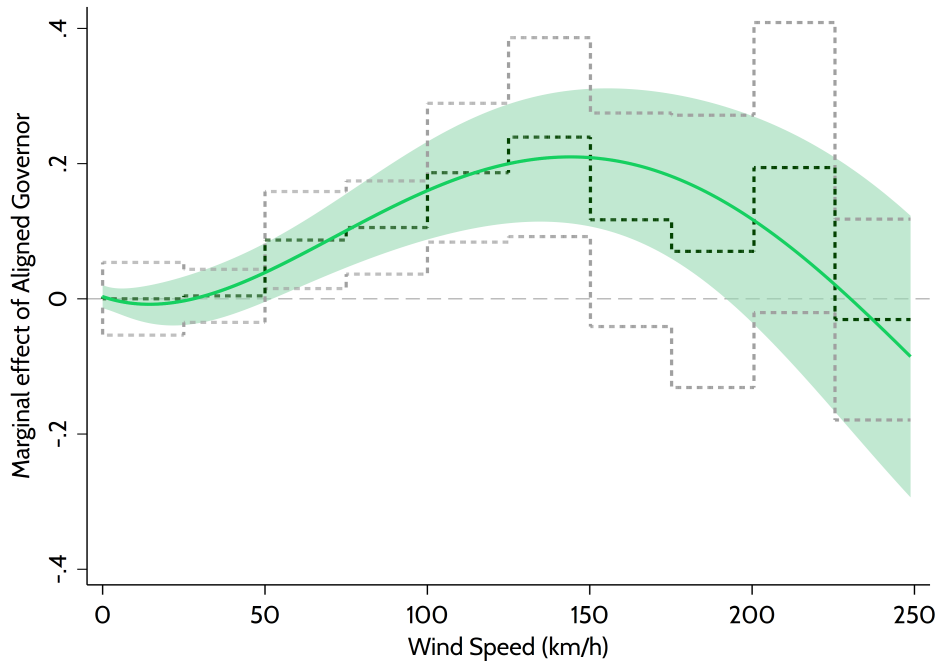


Figure 3: **Alignment Bias for Different Levels of *Wind Speed***

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from the polynomial estimation (solid green line) and the semi-parametric approach (dashed dark green line). The marginal effects correspond to the estimated difference in the probability to receive a disaster declaration due to party alignment. The light green shaded area and the dashed gray lines represent 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level. The sample covers 85,309 county-year observations from 1965–2018.

regression) and all individual *Wind Speed* bins (for the semi-parametric approach), we examine the alignment bias in a nuanced way and find a much more differentiated pattern of political influence.

Figure 3 shows marginal effects of *Aligned Governor* for observing a disaster declaration at different levels of *Wind Speed*.³⁰ The marginal effects, both in the polynomial (solid green line) and the semi-parametric bin approach (dashed dark green line), take the hypothesized hump-shaped form. As expected, coefficients in the semi-parametric step-function vary more wildly, but the estimates are quantitatively similar. While point estimates are close to zero and insignificant for weak wind speeds, the marginal effects of alignment increase with storm intensity, becoming significant at the 95% confidence level at around 52 km/h (32 mph) in the polynomial estimation. These are typically non-catastrophic situations in which the president issues emergency declarations to ensure the functioning and quick repair of damaged crucial infrastructure or to organize local evacuations. The highest alignment effects arise for 144 km/h (89 mph) in the polynomial and the 125 km/h (78 mph) to 150 km/h (90 mph) interval in the semi-parametric approach. At its maximum, the estimated marginal effect is 0.21. This

³⁰We calculate marginal effects and standard errors using the `predictnl` command in Stata. Marginal effects for *Aligned Governor* are derived from the main effect and the *Wind Speed* interactions ($\beta + \delta_1 \text{Wind Speed} + \delta_2 \text{Wind Speed}^2 + \delta_3 \text{Wind Speed}^3 + \delta_4 \text{Wind Speed}^4$).

is about eight times higher than the average relationship from Table 2, which underlines the scope of heterogeneity present in political effects. Marginal effects decrease again for stronger wind speeds, turning insignificant for observations higher than 192 km/h (119 mph).

The importance of accounting for the distinct heterogeneity of the relationship also becomes evident when making a back of the envelope calculation of the associated relief payments. Using the predicted amount of disaster relief in a county for a certain storm strength, its probability distribution, and the previously calculated nonlinear political alignment effect, we calculate that the political component of hurricane relief amounts to roughly USD 500 million per year. This corresponds to about 11.5% of the estimated total annual hurricane relief paid out by FEMA on average (FEMA, 2019b). Note that this figure only contains FEMA's public assistance and individual assistance but no other spending categories such as, for example, hazard mitigation. Our calculation must therefore be considered a lower-bound estimate. A holistic approach to quantifying the total political bias would need to also include, for instance, the difference in long-term costs due to the presence or absence of initial relief and potential indirect costs (cf. Davlasheridze et al., 2017; Deryugina, 2017). Notably, if we used the constant alignment effect for all disasters from Table 2, the resulting political relief share would only total about one-third of the result we obtain with our nonlinear model.

To better understand the economic significance of our heterogeneous political alignment effect, we draw a comparison to the political economy literature on the allocation of U.S. federal spending. Analyzing a wider range of federal funds, the results of Larcinese et al. (2006) correspond roughly to a 2.7% increase in federal funding due to gubernatorial alignment with the president. Albouy (2013), Berry et al. (2010), and Kriner & Reeves (2015) all find increases in the order of 4% for aligned federal politicians in high-variation government spending programs. Although accurate comparisons of studies are impossible due to the different spending categories, our average estimate indicates a similar magnitude (see Table 2). However, if we account for the nonlinear nature of the relationship, we find a substantially higher political and economic relevance.

The results demonstrate that the alignment bias is in fact negligible when locations experience very weak or extremely strong wind speeds. It seems hardly possible for a politician to declare an event a disaster if the impact was not destructive, even if party politics yield incentives to do so. Similarly, it seems also politically impossible to deny a county a declaration in the case of a catastrophic hurricane impact. However, the middle of the wind speed spectrum shows where presidents use their discretionary power to declare disasters. Counties experiencing such wind speeds typically are not hit by the eye of the respective hurricane but are still affected by its wind field, rainfall, and potential flooding, which results in damage to property. These are typically counties not hit by the eye of the respective hurricane but

still being affected by its wind field, rainfall, and potential flooding resulting in damage of property. These situations leave political actors with the most leeway: if presidents are undecided about whether to declare a disaster because a county experienced intermediate damage and either decision would be politically justifiable, the importance of party affiliation increases and more likely becomes the factor to tip the scales.³¹

Despite the length of our 54-year sample period, the number of hurricane events is limited. We conduct resampling-based randomization inference to show the robustness of our findings beyond the alternative conventional one- and two-way clustering choices that we document in Appendix Figure J1. We run a simulation in which we randomly reshuffle the alignment status between years within each state (i.e., keeping constant the number of aligned years within a state and ensuring that all counties of a state still share the same alignment status in the same year). This randomization approach provides a way to validate that our distinct hump-shaped pattern does not arise for placebo allocations of political alignment. Figure 4 displays the estimated marginal effects from 1,000 regressions with the random placebo treatments in gray and the true alignment status in green for comparison. For intermediate wind speeds, all effects of the placebo simulations fall short of exceeding the estimated marginal effects using the actual alignment status. For most simulated runs, the effect is close to zero for low and intermediate wind speeds. Extremely high values of *Wind Speed* are rare, and, therefore, the simulations fan out on the right. This larger spread represents the higher uncertainty of our estimate due to the lower frequency of high-intensity hurricanes (cf. Figure 2 and Appendix Figure E3).

Similar to the procedure for the synthetic control method that Abadie et al. (2015) propose, we can use the simulated coefficients for randomization inference and calculate a permutation p -value for our estimate at different levels of *Wind Speed*. To this end, we divide the number of runs for which the absolute value of the placebo alignment effect $\beta_{i,placebo}$ exceeds the estimates β using the true data at each *Wind Speed* by the total number of simulations N :

$$p_{perm.} = \frac{1}{N} \sum_{i=i}^N \mathbb{1}[|\beta| < |\beta_{i,placebo}|].$$

³¹The focus of our contribution is on the alignment bias in declaration decisions. It is also interesting but beyond the scope of our paper to evaluate to what degree politicians actually benefit from issuing declarations (see previous studies by Gasper & Reeves, 2011; Healy & Malhotra, 2009; Reeves, 2011). In Appendix Figure K2, we provide correlational evidence in line with their findings. This is naturally a noisy and inconclusive estimation because we only cover one disaster type and many other relevant influences enter the vote decision within the four years of a presidential term. However, the figure shows that there exists a correlation between issuing a declaration and the change in the president's county vote share in the next election. Being negative and insignificant for weak wind intensities, the relationship is positive and significant for strong hurricanes. If presidents do not issue a declaration for intense disasters, they lose votes. Qualitatively, this result also fits our assumptions about voter behavior in the theory section, with declarations for higher wind intensities being associated with a higher electoral reward.

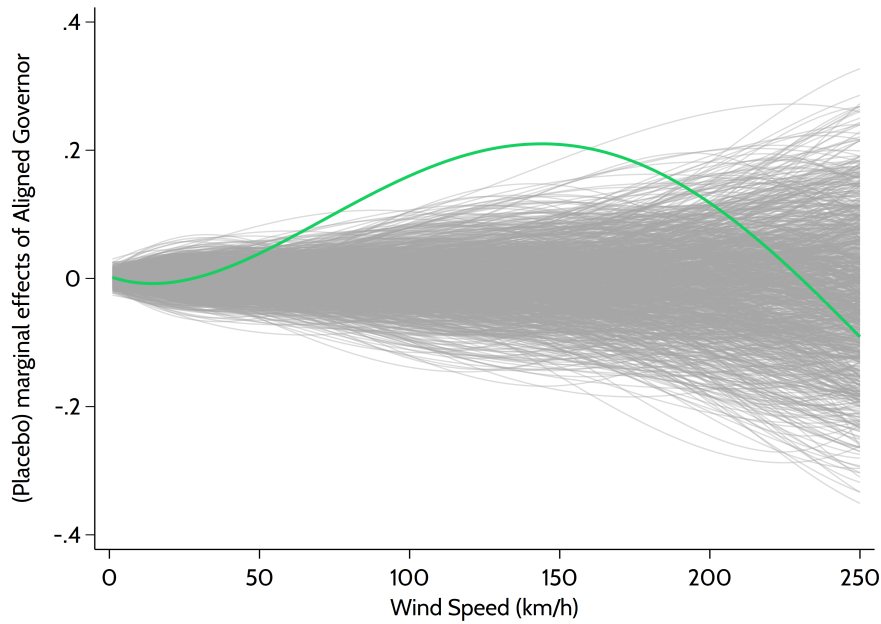


Figure 4: **Randomization Inference**

The figure displays the estimated marginal effects using the true data in green. The gray lines represent marginal effects from each of the 1,000 regressions with the placebo treatments. Placebo simulations were computed with our polynomial baseline regression. For each simulation run, we randomly reshuffle governor alignment status but keep the structure of the panel; i.e., we assign the same placebo treatment to all observations from a state within a year, and we keep the total number of treatments per state as in the original data. Appendix Figure J2 shows a graphical representation of the permutation p -value ($p_{perm.} = N^{-1} \sum_{i=i}^N \mathbb{1}[|\beta| < |\beta_{i,placebo}|]$).

We hence obtain a permutation p -value for every *Wind Speed* level and can derive the 95% confidence interval therefrom (see Appendix Figure J2). Based on this randomization inference approach, *Aligned Governor* has a positive and significant effect in the *Wind Speed* interval [55, 190] km/h, which is very close to the interval [52, 192] km/h that we received from applying conventional two-way clustering to the standard errors (see Figure 3).

5.3 Sensitivity and Robustness

Before analyzing further heterogeneities of the political mechanism, we study the robustness of our main result. The results of the polynomial approach are qualitatively similar when we use different polynomials. Appendix Figure J8 shows marginal effects for polynomials of the third to ninth degree. As derived in Section 4, we use the fourth-degree polynomial as a baseline. To ensure clarity of the graphical representation, the following multi-panel figures display marginal effects only for the fourth-degree polynomial approach given that all flexible estimations, including the semi-parametric approach, yield similar results.

Despite the chaotic trajectories of hurricanes, which randomly select politicians to make a decision on disaster relief, a remaining concern for our identification is the endogeneity of the political-economic

process that results in the alignment patterns we observe. We want to rule out that any unobserved factors that potentially systematically explain both alignment and declarations and that are not yet captured by fixed effects, time trends, and controls bias our estimates. We study whether our results hold in situations where political alignment is quasi-randomly determined, i.e., in subsamples characterized by close electoral outcomes. A vast literature studies discontinuities created by electoral thresholds (e.g., Broilo & Nannicini, 2012; Curto-Grau et al., 2018; Eggers et al., 2015; Pettersson-Lidbom, 2008). In our case, political alignment changes if a politician from the opposite party wins one of the two offices. For instance, *Aligned Governor* discontinuously switches from 0 to 1 as soon as the candidate from the opposition party receives more votes in the election than the aligned incumbent governor. We can therefore use state-level electoral outcomes to define situations in which governors are just aligned or just

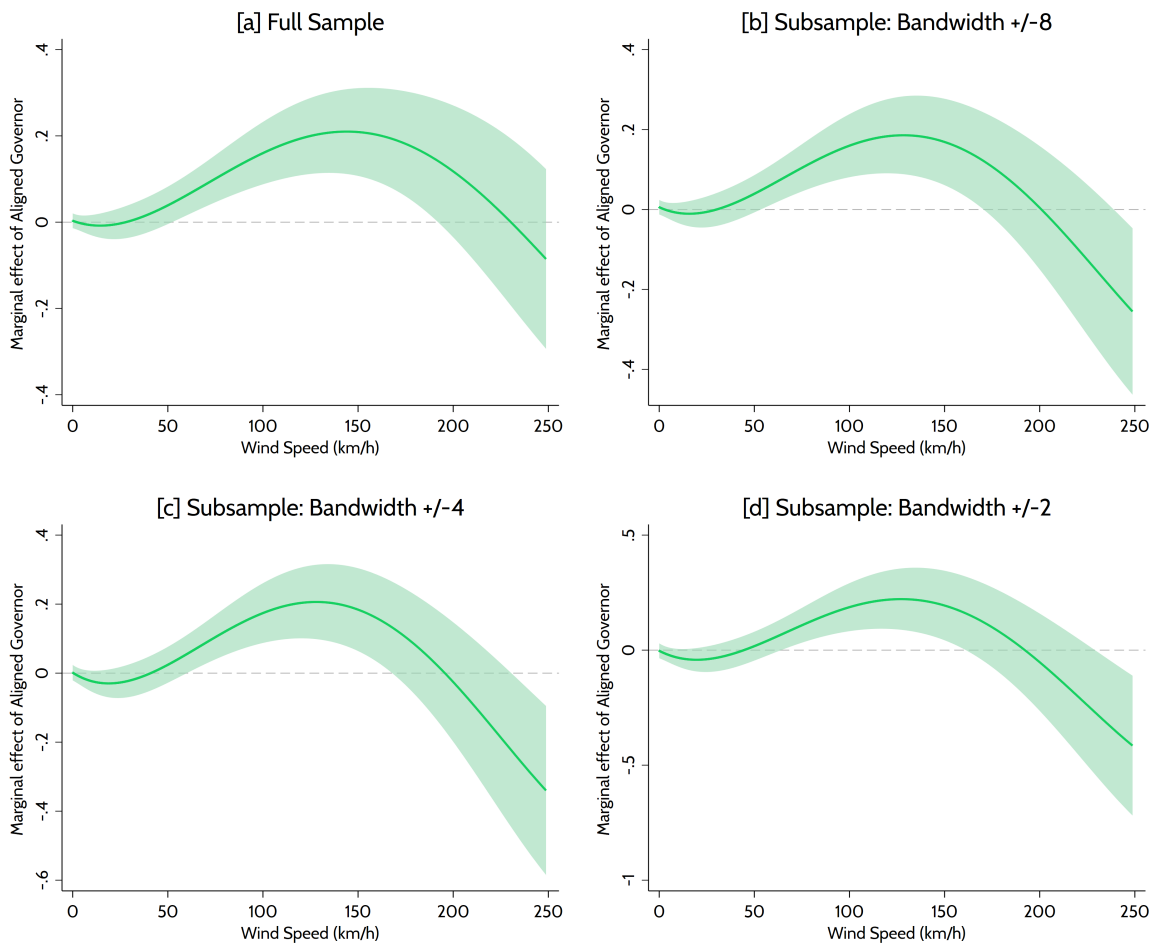


Figure 5: **Robustness: Close Elections Subsamples**

This figure shows the sensitivity of our result in subsamples with different electoral margins from the previous elections. The panel titles [b]-[d] depict the respective bandwidths, by which we restrict the samples. The bandwidth corresponds to half the difference in percentage points that would have been necessary to flip the alignment status. The panels display marginal effects of *Aligned Governor* for different levels of *Wind Speed*. The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level.

unaligned with the president by a small margin.³² Figure 5 displays the results for different bandwidths of close election outcomes. The results turn negative and significant for extremely high wind speeds. Otherwise, the estimates in the restricted samples are quantitatively similar to the full sample.

Similarly, we test how the alignment bias differs with regard to how close a governor won the previous election. Presidents might behave more generously in providing declarations to medium-affected counties if they think their co-partisan governor needs an additional boost to secure reelection. Analogously, governors might also request relief more often in these situations. Based on past statewide election outcomes, we split the alignment variable into four dummies defined by different gubernatorial margins of victory. Figure 6 shows that the relationship tends to be stronger for governors with narrower margins of victory. While the alignment effect arises in all instances, it is significantly positive in a broader *Wind Speed* range for governors who faced more competitive elections.³³

The main estimation approach assumes that a certain level of wind speed corresponds to equal need for a disaster declaration at each location. However, regions with a higher hurricane frequency might be more resilient to higher wind intensities. To demonstrate that our results do not depend on the assumption of a nationwide uniform resilience level, we allow separate *Wind Speed* effects for each state. Panel [a] of Appendix Figure J9 indicates that the marginal effect estimates of our main specification remain essentially unchanged.

As different regions may have developed in divergent ways over the course of our 54-year long panel, we want to control for the possibility that this influences our findings. We employ county \times decade fixed effects to account for within-county changes over time in a more flexible way than using linear time trends. This specification results in a slightly wider confidence interval (see Panel [b] of Appendix Figure J9).

The chaotic nature of hurricanes can result in wildly erratic treatment patterns, and one might be concerned that particular states or time periods drive our results. To alleviate these reservations, we run 48 regressions, each excluding all observations from one individual state at a time. Panel [a] of Appendix Figure J3 exhibits that dropping individual states in no case results in a major difference from

³²In addition to tight outcomes in gubernatorial elections, the U.S. winner-takes-all system in combination with the electoral college produces situations in which the electoral votes from one or few close states are pivotal for the outcome of the presidential election; take, for instance, the 2000 Bush vs. Gore election outcome in Florida. We account for these quasi-random alignment outcomes when defining our respective close-election subsamples. We assign observations either the margin of victory of the most recent gubernatorial election or the respective margin of victory from the closest state that would have tipped the respective presidential election if this margin was closer. The broader the bandwidth, the more observations from the full sample remain in the respective restricted subsample.

³³In Appendix Figure J7, we restrict the analysis to a subsample of states where there was a switch of the party receiving the majority of the statewide votes in one of the last three presidential (Panel [a]) or gubernatorial elections (Panel [b]). In Panel [a], the peak of the alignment effect shifts to a somewhat higher *Wind Speed*, but otherwise the relationship in swing states is not significantly different from what we find for the full sample.

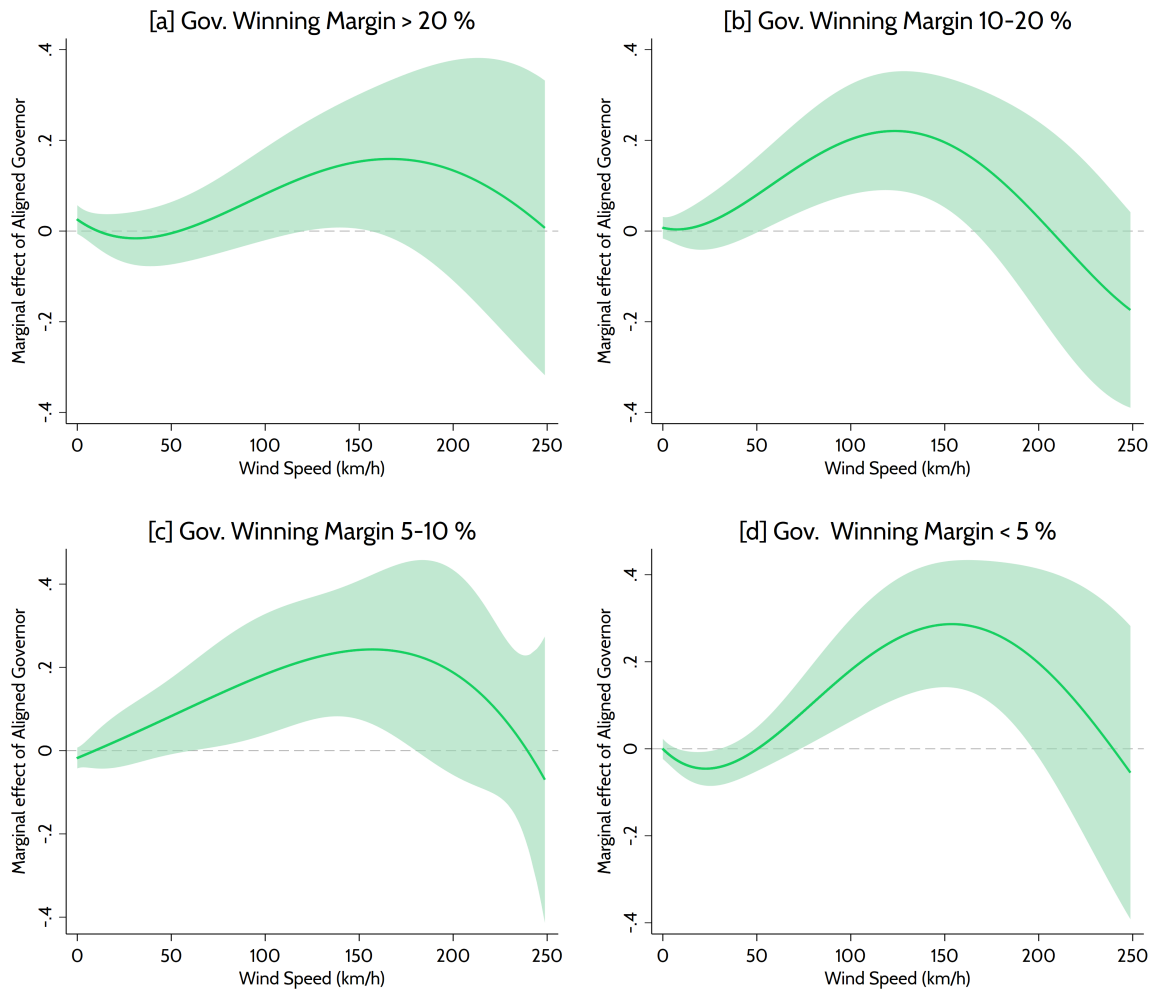


Figure 6: Alignment Effects for Governors with Different Margins of Victory

This figure illustrates how the alignment effect depends on the margin of victory (MOV) of the requesting governors. The solid green lines in the four panels display marginal effects of separate *Aligned Governor* indicators (depending on the margin of victory) from one joint regression. Panel [a] shows the marginal effect of *Aligned Governor* if the governor’s statewide MOV in the previous election was larger than 20 percentage points; Panel [b] for MOV between 10-20, Panel [c] for MOV between 5-10, and Panel [d] for MOV smaller than 5 percentage points. The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level.

the baseline. We apply the same approach to individually omit each of the six decades that our data cover. Likewise, the result is robust to excluding individual decades.

Coastal counties are generally more strongly affected by hurricanes and face the additional hazard of storm surges. To test whether the relationship is driven by counties that face a higher baseline risk of hurricane strikes, we split the sample into coastal and non-coastal states. We use the definition of coastal watershed counties from NOAA, excluding non-Atlantic and non-Gulf counties in accordance with Strobl (2011). Appendix Figure J5 shows that the political bias is significantly positive in both samples but is in fact stronger in non-coastal counties. For almost all hurricanes, non-coastal counties experience less damage than coastal counties. The coast thus receives the most public attention regarding the event,

and politically driven relief allocation is less feasible there. However, the president can include more inland counties in the disaster declaration and base this decision partly on partisan considerations.

We run a series of further robustness tests. If we restrict the sample to cover only emergency declarations or the more comprehensive major disaster declarations (see Appendix Figure J4), the maximum marginal effect for major declarations corresponds to stronger hurricane intensities than for emergency declarations. Estimates for extreme wind speeds for emergency declarations are noisier as the president rather issues this declaration type to ensure a quick response in non-catastrophic situations. However, both disaster types are subject to the alignment bias for intermediate hurricane intensities. Adding an additional variable that controls for the yearly frequency of hurricanes in each county (see Panel [a] of Appendix Figure J11) does not change the results. In Panel [b], we replace the *Wind Speed* variable with the damage index proposed by Emanuel (2011). Given the assumptions of the damage index (see Appendix E), the results are qualitatively and quantitatively similar.

We further increase the flexibility of our specification by allowing polynomial interactions of alignment with the other hurricane damage measures (*Rainfall* and *Storm Surge*) in Panel [a] of Appendix Figure J13. In Panel [b], we include interactions of *Aligned Senators* and *Aligned Representatives* with the *Wind Speed* polynomial. Panel [c] allows for all interactions together. Neither specification alters the results substantially. In Panel [d] of Appendix Figure J13, we additionally control for non-hurricane-related disaster declarations in the respective counties as one potentially omitted factor, but the estimate of *Aligned Governor* does not change. This result is not surprising as the occurrence of hurricanes is orthogonal to other disasters and the existing political or economic conditions in a county.

Likewise, the results are not sensitive to adding a vector of socioeconomic controls (Panel [c] of Figure J11), using satellite-based rain and temperature controls on the county level (Panels [d] and [e] of Figure J11), and excluding the hurricane-related *Rainfall* and *Storm Surge* data (Panel [f]). In Appendix Figure J12, we control for the influence of long, persistent past hurricane shocks and declarations directly by adding 10 lags of *Wind Speed* (Panel [a]) and 10 lags of the dependent variable *Declaration* (Panel [b]). Both estimations yield basically the same result as our main model. Our results are also robust to alternative sample definitions. Including only observations with a positive *Wind Speed* (Figure J5, Panel [c]) and using a fully balanced panel of all contiguous U.S. counties (Panel [d]), which inflates the number of zero observations, yields the same marginal effects pattern. The results also prove robust to excluding outliers with high leverage, i.e., above Cook's distance cut-off, and without low- or high-intensity hurricanes (see Appendix Figure J6). To summarize, none of the robustness tests yields evidence against the existence of the alignment bias.

5.4 Additional Political Influences and Relief Cycles

As we find an alignment bias in the allocation of disaster declarations for medium hurricane intensities, we analyze further sources of political influence in this section.

The presidents might take political factors other than their alignment with the governors into account. We estimate the heterogeneous impacts of *Aligned Representative* and *Aligned Senators* – political actors who are not directly involved in the declaration process – analogously to *Aligned Governor* previously. The results are statistically weaker, but, qualitatively, the same pattern emerges: the relationship is positive and significant only for intermediate *Wind Speed* observations and is insignificant for both low and high storm intensities (Figure 7, Panels [a] and [b]).³⁴

From an electoral strategy perspective, the geographical distribution of different groups in the electorate is pivotal. To win an election and secure majorities in the United States' first-past-the-post system, politicians need their core supporters to turn out and try to win in contested areas. Two hypotheses from the distributive politics literature, the so-called core and the swing voter hypothesis, suggest that politicians therefore have incentives to target these areas when they try to exert tactical redistribution (e.g., Cox & McCubbins, 1986; Lindbeck & Weibull, 1987). Neither hypothesis predicts that strongholds of the opposition party are favored.

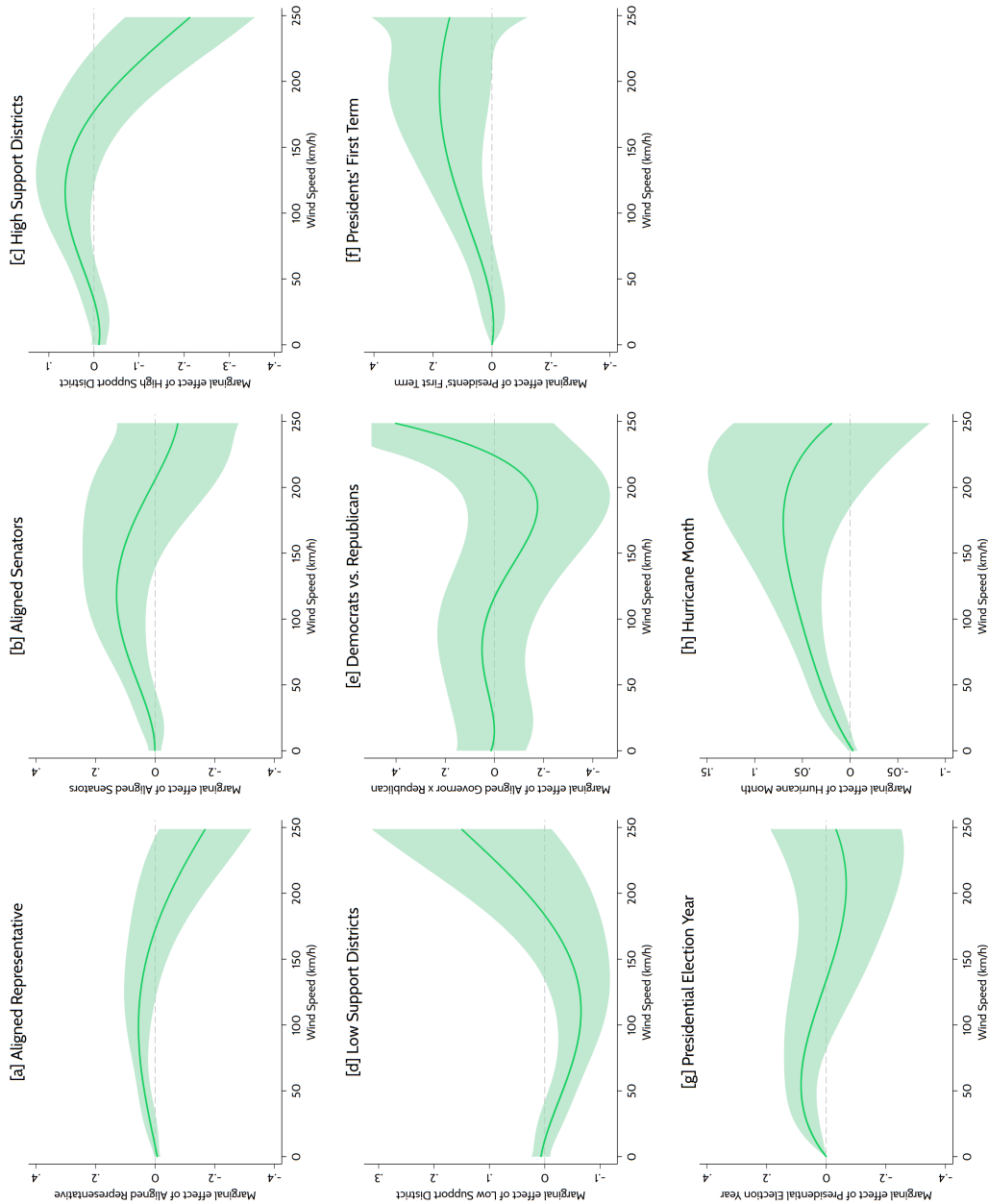
To test these propositions, we interact dummy variables for counties that fall in *High-Support Districts* and *Low-Support Districts* of the incumbent president's party from recent congressional elections with the wind speed polynomial.³⁵ Panel [c] of Figure 7 indicates that for high-support districts, the marginal interaction effects are positive and slightly significant only for a narrow *Wind Speed* range but again showing the characteristic hump-shaped pattern. In contrast, counties in *Low-Support Districts* (Panel [d]), *ceteris paribus*, have a significantly lower probability of receiving a disaster declaration for intermediate storm intensities. For low-support counties, the marginal effects curve shows exactly the opposite shape. The estimations yield a significant negative effect for medium disasters. This suggests that presidents do not perceive investing political capital in counties whose citizens are unlikely to help them to win an election as a winning strategy, which is in line with both the core- and the battleground-hypothesis.

³⁴In Appendix Figure J10, we use *Alignment Count* as an alternative to the three individual variables. It represents the number of key politicians (i.e., governor, representative, and senators) aligned with the president. For this count variable, we receive a significant result that is qualitatively similar to that for the politicians individually.

³⁵We code *High-Support Districts* as those where the incumbent president's party candidate received more than 60% of the two-party vote share in the previous congressional election. *Low-Support Districts* represent those where they won less than 40%, respectively. We use results from the congressional elections for this analysis because redistricting creates additional orthogonal variation. While much of the variation on the county and state level for the other elections is captured by county fixed effects, counties occasionally belong to different congressional districts with different levels of electoral competition over the course of our 54-year sample period.

Figure 7: Heterogeneous Political Effects

The figure displays marginal effects for the variables of interest depicted on the vertical axes from eight polynomial regressions. The green shaded areas represent 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level. In each specification, we add the respective variable of interest as well as its interactions with the *Wind Speed* polynomial to our baseline for the estimation of heterogeneous effects. In Panel [c] *High-Support District* is an indicator that takes the value 1 if the candidate from the party of the incumbent president received more than 60% of the two-party vote share in the previous congressional election; *Low-Support Districts* in Panel [d] are those where the president's party received less than 40%. Panel [e] plots the difference of the alignment effect between Republicans and Democrats based on a triple interaction. In Panels [f] and [g] *Presidents' First Term* and *Presidential Election Year* are indicators for a president's first term and presidential election years, respectively. In Panel [h], *Hurricane Month* depicts the month in which the hurricane causing the strongest *Wind Speed* in each county and year occurred.



Another obvious characteristic to distinguish is the effect of aligned governors for the two major parties, Republicans and Democrats. To test this effect, we further interact *Aligned Governor* with an indicator for being in the *Republican* party. Panel [e] of Figure 7 displays the differences of the alignment effect for Republicans and Democrats from this triple interaction. The differences are insignificant. As our swing state subsample (Appendix Figure J7) already suggested, the alignment bias does not appear to be attributable to a single party.

If the reason for the observed political bias is electorally motivated, one would expect the relationship to become potentially stronger in election years. In Panels [f] and [g] of Figure 7, we interact the *Wind Speed* polynomial with a dummy variable taking the value 1 in a president's first term [f] and presidential election years [g], respectively. Both regressions show that presidents are, *ceteris paribus*, more likely to issue a disaster declaration for medium wind speeds in their first term and for low wind speeds in election years as compared to other years.³⁶

The hurricane season ranges from June to November, with most of the strongest storms occurring from August to October. Major elections in the United States usually take place in early November. To exploit this fact, we additionally collected data on the month in which the strongest hurricane-related *Wind Speed* occurred in each county and year. By interacting a linear variable for *Hurricane Month* with the *Wind Speed* polynomial, we see that – for the same levels of *Wind Speed* – storms that occur later in the year are related to a higher probability of a disaster declaration. One possible explanation for the seasonal variation of more declarations in the fall could thus be a within-year political alignment cycle, where presidents tend to declare more disasters closer to elections. However, one can, of course, still find alternative explanations for both between and within-year political budget cycles (cf. Eichenauer, 2020), and the previous tests alone are not more than indicative.

To show more convincing evidence for the existence of political budget cycles in U.S. disaster relief, we pursue two strategies: a placebo test for the within-year cycle, because *Hurricane Month* should only play a role in election years, and a comparison of the alignment bias between election and non-election years, as our theory predicts stronger alignment effects in election years. For both tests, we need to run regressions including triple interactions. That is, we now interact the quartic *Wind Speed* polynomial with two political variables of interest at once. For the regressions shown in Panels [a] and [b] of Figure 8, we add the expression $\sum_{b=1}^4 (Wind\ Speed_{i,t}^b \times Aligned\ Governor_{s,t} \times Election\ Year_t)$ to the estimation equation. For Panel [c] of Figure 8, we add the term $\sum_{b=1}^4 (Wind\ Speed_{i,t}^b \times Hurricane\ Month_{i,t} \times Election\ Year_t)$ to our model.

³⁶These estimates might hinge on seasonal anomalies. We show them for completeness before we analyze election-year effects in more detail by using triple-interactions in Figure 8.

Panel [a] of Figure 8 shows the results of the triple interaction regression by plotting the marginal effect of *Aligned Governor* on the vertical axis. The graphic distinguishes alignment effects by *Presidential Election Year* (equaling 1 in election years, dashed blue line, and 0 in non-election years, solid green line). Panel [b] does the same for *Any Election Year*, an indicator additionally accounting for congressional and gubernatorial election years. In both panels, the relationship emerges in all years, but the estimate of the alignment effect is larger and more significant for election years than for non-election years.

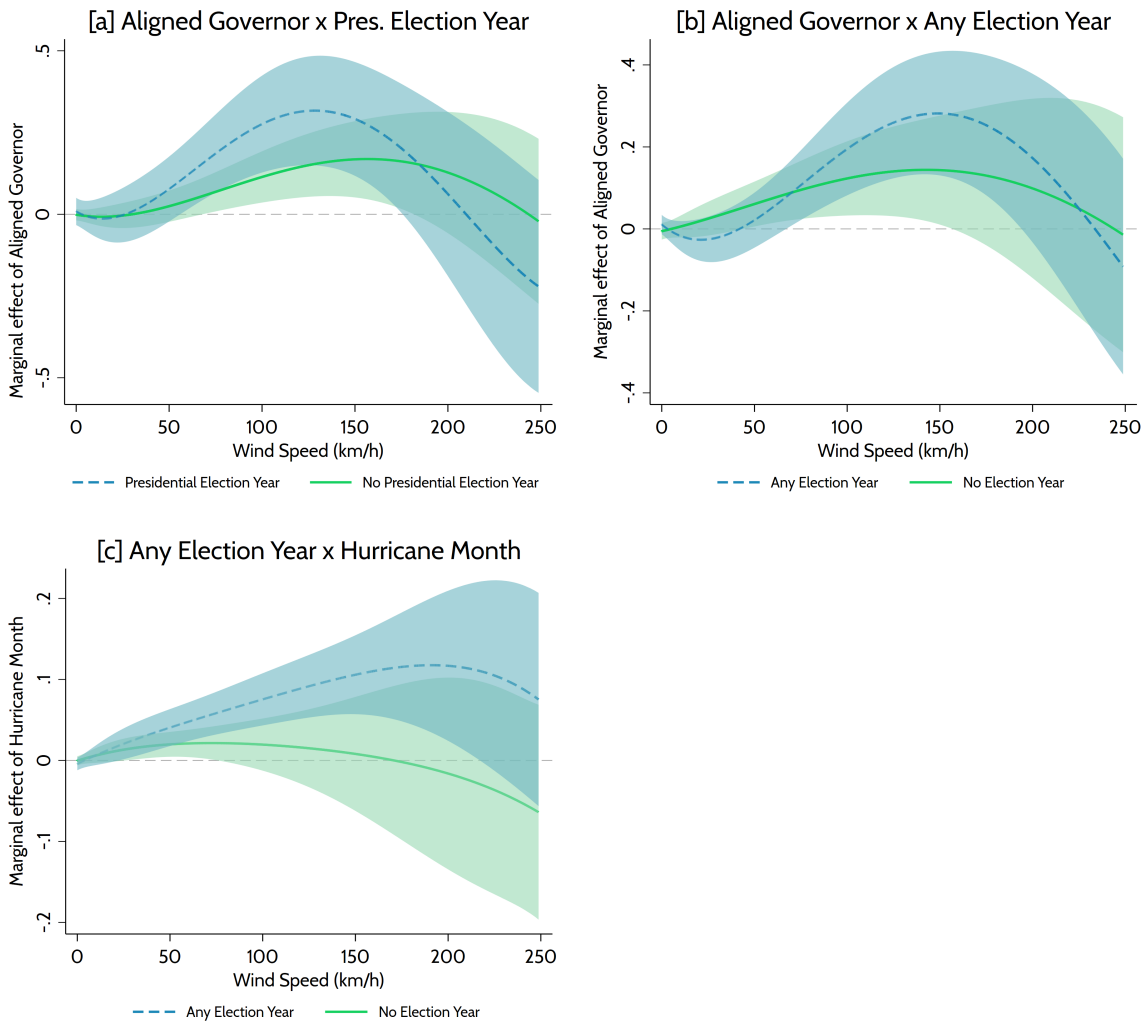


Figure 8: Political Relief Cycles – Marginal Effects from Triple Interactions

The figure displays marginal effects for the variable specified on the respective vertical axis from three polynomial estimations including triple interactions. In each specification, we add the depicted variables of interest as well as all possible cross-interactions with the *Wind Speed* polynomial to our baseline for the estimation of heterogeneous effects. Shaded areas represent 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level. In Panel [a] the dashed blue line displays marginal effects of *Aligned Governor* in presidential election years. The green solid line shows the estimated effect of *Aligned Governor* if *Presidential Election Year* equals 0. In Panel [b] the dashed blue line displays marginal effects of *Aligned Governor* in years of major elections (i.e., presidential, gubernatorial, or congressional elections). The green solid line shows the estimated effect of *Aligned Governor* if *Any Election Year* equals 0. In Panel [c] the dashed blue line shows the effect of *Aligned Governor* in election years. The green solid line displays the estimated effect of *Hurricane Month* if *Any Election Year* equals 0. Appendix Figure J14 plots the marginal effects of the differences of the two curves in all three panels.

However, Appendix Figure J14 shows in Panels [a] and [b] that the difference between both curves is not significant.

Considering within-year political alignment cycles, Panel [c] of Figure 8 tests how the month effect differs for election years (dashed blue line) and non-election years (solid green line). In non-election years, the estimated effect of *Hurricane Month* is close to zero and insignificant. In election years, however, it is positive and significant for intermediate storm intensities. Panel [c] of Appendix Figure J14 shows that this triple interaction yields a significant difference for the within-year declaration cycle between election years and non-election years. That is, hurricanes of equal intensity have a higher probability of being declared a disaster if they occur in a later month, but only in election years. The rationale here is that promising generous relief potentially has a higher leverage effect if the disaster is a salient topic just before an election.

All results contribute to the notion that there exists a political (alignment) bias in U.S. disaster relief. We find a robust nonlinear pattern of partisan relief allocation. Political effects are most prevalent for medium-intensity hurricanes. Our analysis demonstrates that one must look beyond average effects to understand the specifics of political influence in this domain. In our concluding remarks, we discuss how these findings add to our understanding of executive politicians' behavior and how they matter in terms of policy implications.

6 Conclusion

We analyze the political economy of disaster relief, employing a novel hurricane damage data set and focusing on hurricane-related disaster declarations in the United States from 1965–2018. Based on a simple theoretical framework, we show that the issuance of disaster declarations involves a political bias: counties with a governor who is a co-partisan of the incumbent U.S. president, on average, have a significantly higher probability of receiving a federal disaster declaration. The main contribution of our study stems from the empirical analysis of nonlinearities in political alignment effects from applying flexible interaction models. We find a persistent nonlinear alignment bias where presidents only use their discretion strategically for hurricanes of medium intensity. While political influence only plays a minor role on average, strategic political considerations are about eight times more relevant for medium-intensity storms. Furthermore, self-interest and party political motivations seem to drive the results since we find stronger effects in election years and for hurricanes closer to elections in November. The alignment bias is most pronounced when the potential political returns are highest. Our results prove robust to adding county-specific time trends, lagged dependent variables, other covariates and their lags; and omitting individual decades, states, or hurricane outliers.

The results from our analysis show the necessity of accounting for possible effect heterogeneities in analyses of political-economic relationships. By disregarding the complexity of political-economic relationships in statistical estimations, the actual nexuses remain potentially concealed and the economic consequences underestimated: while our hump-shaped continuum for the marginal effects of political alignment corresponds to annual political hurricane relief spending of about USD 500 million, conventional average estimates for the same calculation would only suggest about one-fifth of this amount. Generally speaking, political influence may depend more on the specific constellations and opportunities that politicians face than previously revealed. Regarding disaster relief, we show that politicians do not necessarily require the occurrence of random third events that distract the public attention from their strategic actions. They can exploit specific ambiguous decision-making situations that arise within the impact range of a single disaster event in a biased manner. The results from our analysis imply by no means that politicians are not responsive to the needs of the electorate. In situations that clearly require a certain decision, we do not find evidence for political biases. However, we observe that democratic control of political actors does not prevent favoritism in ambiguous decision situations, particularly if they expect a high electoral return. Politicians behave strategically if the situation allows. As we show, the degree of opportunity for strategic behavior can be very heterogeneous.

The resulting question is whether the functional form assumptions in political-economic analyses in general tend to oversimplify the true underlying processes by neglecting potentially nonlinear relationships. As the heterogeneous effects are substantial and persistent with regard to disaster assistance, future research should evaluate whether our findings are generalizable to other political-economic research areas. Potential relationships include various distributive policies where spending allocations involve a certain conditionality or eligibility criteria, e.g., in the EU, in international organizations, or in international aid. Whenever it is not clear that, for instance, certain domains in an economically underdeveloped region should receive supportive funding, political considerations have a higher potential to become the factor to tip the scales. It is important to acknowledge that our findings are not necessarily externally valid for other spending areas; but they change our *a priori* assumptions when observing comparable processes, where a lack of transparency or data availability prevents credible empirical testing.

As our findings indicate inefficiency in the disaster relief system, there are certain direct policy implications. The current mechanism makes ex-post spending more attractive for politicians than investing in preparedness, which creates a moral hazard problem. Ex-post relief is directly visible and better suited as a political tool than preparedness spending because the benefits of preparedness only emerge in the

long-run and are not directly attributed to the politicians.³⁷ A loan-based system, higher state cost shares, more local responsibility, or payments conditional on states' preparedness efforts would make relief a less politically attractive instrument (cf. [Platt, 1999](#), p. 290; [Lindsay & McCarthy, 2015](#)).

In addition to these commonly suggested improvements, we propose institutional changes to address political influence in the disaster declaration process. First, technical improvements such as better satellite imagery would allow effective data-based issuance of declarations for disasters. In general, more rule-based criteria for disaster declarations or formulas derived from measures of affectedness and need would constitute an improvement, promoting fairness, predictability, and transparency. Second, as we do not find politicized spending patterns in the case of extreme events, the president could remain in charge of these events to ensure a quick disaster response. For intermediate cases or situations that might require a declaration not meeting predefined thresholds, the president should be required to request a mandate from an independent expert commission. Third, a sensible approach might be to depoliticize disaster declarations (cf. evidence by [Bostashvili & Ujhelyi, 2019](#), on civil service reforms) and assign declaration authority to a suitable and skilled bureaucrat, comparable to a central banker, who does not have to run for reelection.

Admittedly, the probability for substantive changes to the process in the currently polarized political situation in the United States is low. The Senate and president have blocked past reform attempts ([Sylves, 2008](#), pp. 100–101). While the U.S. relief system might not be easy to reform, countries that aim to set up or improve a system of disaster relief may draw the necessary conclusions from the existing empirical findings. Policy implications particularly concern the many developing countries that are highly exposed and prone to various natural hazards. The need to design an efficient disaster preparedness and relief system is reflected in the fact that the urban coastal population – and therefore the vulnerability to hurricanes – is projected to continue growing.

Improving resilience to natural disasters, which are expected to increase in severity in the course of climate change, will certainly constitute a major challenge of the 21st century. As [Strömberg \(2007](#), p. 212) notes, “it is essential that relief be given where it can do most good.” A key component to ensuring this is a well-functioning system of disaster relief. Disasters would then not constitute an opportunity for political gain, but rather an opportunity to observe the advantages of a modern welfare state in disaster recovery.

³⁷Research shows that the government could reduce the need for ex-post spending by showing appropriate preparedness action. [Davlasheridze et al. \(2017\)](#) calculate that a 1% increase in ex-ante spending would reduce future damage by 2%. [Healy & Malhotra \(2009\)](#) estimate that USD 1 spent on preparedness mitigates future damage by USD 15. A second moral hazard problem emerges among local governments and individuals in highly exposed regions. If they have hope that the government will bail them out (particularly in a favorable political constellation), they have an incentive to underinvest in preparedness and insurance, which increases disaster vulnerability.

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All internet sources last accessed on August 18, 2020 if not stated differently.

Online Appendix

A	Disaster Relief in the United States of America	47
A.1	Brief Historical Review	47
A.2	The Disaster Declaration Process	47
A.3	FEMA Programs and Disaster Relief Funding	49
B	Further Theoretical Considerations	51
C	Hurricanes	54
D	Reported Damage Data – Short Discussion of Criticism in the Literature	56
E	Hurricane Data	57
F	Variable Description and Summary Statistics	61
G	Robustness – Average Estimation Results for the Alignment Bias	65
H	Main Results – Detailed Regression Output Tables for Figure 3	70
J	Heterogeneous Alignment Bias – Robustness and Further Results	73
J.1	Standard Errors and Randomization Inference	73
J.2	Subsamples	75
J.3	Alternative Specifications and Triple Interactions	79
K	Additional Correlations and Results	86
	References	88

A Disaster Relief in the United States of America

A.1 Brief Historical Review

For the first 160 years of U.S. nationhood, the role of the federal government with respect to disaster assistance was minor. Congress had to pass ad-hoc legislation when the federal state decided to provide aid on occasions of catastrophic events (Barnett, 1999). This changed in 1950 when Congress decided to make disaster relief provision an executive responsibility of the president, establishing the system of presidential disaster declarations with the Federal Disaster and Relief Act (Platt, 1999; Sylves, 2008). It “put in place a standard process by which Governors of states could ask the President to approve federal disaster assistance for their respective states and localities” (Sylves, 2008, p. 49). Since then, a federal disaster assistance system has existed, to deliver relief to regions in case state or local capacities are overwhelmed in the wake of natural events such as floods, earthquakes, droughts, fires, hurricanes, or other severe storms (Platt, 1999). The federal role in disaster response and recovery gradually expanded and became the primary source for disaster funding (FEMA, 2017b; Lindsay & McCarthy, 2015). FEMA’s budget for relief payments over the last 10 years (2010–2019) has averaged USD 13.63 billion per year (Painter, 2019).

To bundle the previously scattered responsibilities for federal disaster management, including disaster preparation, mitigation, response, and recovery, under one roof, the Federal Emergency Management Agency (FEMA) was established in 1979 (FEMA, 2017a). The Robert T. Stafford Disaster Relief and Emergency Assistance Act from 1988 constitutes the current legislation for federal disaster relief. Among others, it augmented the discretion of presidents in judging what qualifies for disaster assistance, permits declarations for further classes of natural and certain non-natural catastrophes, and established a hazard mitigation program (Downton & Pielke Jr., 2001; Sylves, 2008). Despite the gradual expansion of the scope of federal disaster assistance and the large number of major and minor amendments to this legislation, the process of presidential disaster declarations has “changed very little over time” (Lindsay & McCarthy, 2015, p. 20).

A.2 The Disaster Declaration Process

Federal disaster relief in the United States is contingent upon a presidential disaster declaration. The president must declare an event a federal disaster before FEMA can start determining the amount of financial assistance and the individuals or entities eligible for relief. If a severe disaster strikes, an affected state must activate its own emergency plan first since the United States follow a “bottom-up”

approach in disaster management (McCarthy, 2014). If the governor then detects that the state and the local resources are insufficient to provide an effective response, they can initiate a preliminary damage assessment (PDA), thereby collecting damage records and unmet needs at the local level (FEMA – EMI, 2017). Thereafter, the governor can formally request federal aid from the president (see FEMA, 2011; 2017b). The official request includes information from the PDA and a description of the disaster impact as well as the state’s efforts to cope with it and an attestation that disaster response is beyond the state’s capabilities. In the letter, the governor also states which counties they believe qualify for federal assistance (FEMA – EMI, 2017, Sylves, 2008, pp. 83–84).

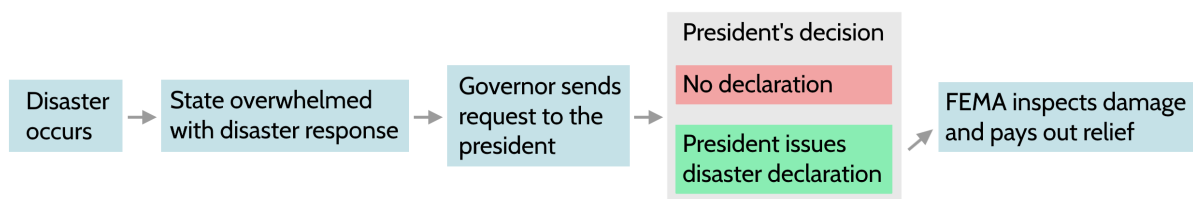


Figure A1: **The Disaster Declaration Process**

Sketch of the main steps in the process of federal disaster declarations in the United States.

In the next step, the White House receives a recommendation from federal FEMA bureaucrats regarding the declaration decision, but it is solely at the president’s discretion whether to declare the event a disaster (Downton & Pielke Jr., 2001; FEMA, 2017b). Presidents have wide discretionary power over which circumstances and areas they declare a disaster and when they deny a request (Sylves, 2008, p. 79).³⁸ Each presidential declaration is issued to a specific state and explicitly lists the counties eligible for federal help under the declaration. Declarations may be statewide, but only a limited number of counties are typically included in the disaster area (Downton & Pielke Jr., 2001; Sylves, 2008).³⁹ In exceptional cases, the president can declare an emergency without a gubernatorial request when “he determines that an emergency exists for which the primary responsibility for response rests with the United States” (McCarthy, 2014, p. 9).

Two types of disaster declarations can be issued by the president: emergency declarations and major disaster declarations (*ibid.*). The *Stafford Act* (1988) defines emergencies as

any occasion or instance for which, in the determination of the President, federal assistance is needed to supplement state and local efforts and capabilities to save lives and to protect property and public health and safety, or to lessen or avert the threat of a catastrophe.

³⁸Presidents are obliged not to use a fixed set of rules for their decisions because “[n]o geographic area shall be precluded from receiving assistance [...] solely by virtue of an arithmetic formula or sliding scale based on income or population” (*Stafford Act*, 1988). FEMA applies certain per capita damage formulas (using data from the PDA) for its recommendation (McCarthy, 2014).

³⁹Sylves (2008, pp. 83–84) explains that “the president [...] may choose to include some but not all of the counties recommended by the governor.” If necessary, counties can be added to a declaration within 30 days after the declaration (*ibid.*, pp. 83–88; FEMA, 2017b).

As a supplement to local and state efforts, emergency declarations should ensure a quick response and functioning of essential services (McCarthy, 2014). Emergency declarations have existed since 1974, and they are limited in scope, being restricted to USD 5 million for a single declaration. The vague language of the Stafford Act gives the president significant discretion and often creates ambiguity for governors regarding which situations qualify for emergency assistance (Sylves, 2008, p. 60).

The second category of declarations is the “major disaster declaration,” which makes a wide range of assistance available both for short- and long-term work in response to large-scale disasters (FEMA, 2011; McCarthy, 2014). While major disaster declarations are only issued post-disaster, emergencies are sometimes even declared in anticipation of a severe event, such as the imminent landfall of a strong hurricane, to prepare the post-disaster response and to evacuate particularly vulnerable regions (Lindsay & McCarthy, 2015). A state can thus, in principal, receive a pre-hurricane emergency and a post-hurricane major disaster declaration for the same event: “while federal expenditures may be little different, the number of declarations in these instances is doubled” (*ibid.*). This circumstance influences the choice of the dependent variable. While emergency declarations are financially capped, major disaster declarations can essentially release an unlimited amount of money once they are issued. As long as eligibility requirements are fulfilled, FEMA is entitled to provide support (Platt, 1999, p. 21).

Notably, although “FEMA – not the president – decides how much money to allocate” (Sylves, 2008, p. 101) once a declaration is issued,

the ultimate decision to approve or reject a governor’s request for a declaration is made by the president, not by FEMA officials. In effect, FEMA officials have little leeway in matters of presidential declaration decision-making. (*ibid.*, p. 94)

The sequential procedure of governors requesting and the president granting or denying declarations existed throughout and was stipulated in “[b]oth the 1950 law and the Stafford Act of 1988” (*ibid.*, p. 79).

A.3 FEMA Programs and Disaster Relief Funding

Federal assistance can be divided into public assistance (PA), individual assistance (IA), and the hazard mitigation grant program (HM). PA is FEMA’s largest and most frequently activated program (Lindsay, 2014). Under this program, local government and non-profit organizations receive monetary, personnel, technical, or advisory assistance for removing debris and repairing or replacing various types of damaged public infrastructure (*ibid.*, Sylves, 2008). While federal help was mainly restricted to the initial repair of crucial infrastructure and the distribution of essentials in the 1950s and 1960s, it was complemented

by further programs such as IA (established in 1974), including temporary housing, grants to rebuild, and legal and mental health services, etc. as well as a larger range of possible payments to communities (Lindsay & McCarthy, 2015; Platt, 1999, pp. 15–17).

IA comprises a selection of programs to meet individual and household needs. This may include, for instance, temporary housing, grants to repair and replace uninsured property destroyed by the event, food coupons, crisis counseling, disaster-related unemployment compensation, and help to guarantee the physical or mental health of those affected (DHS, 2018; Lindsay, 2014). FEMA inspectors determine individuals' and public entities' eligibility for relief as well as the exact amount of grants. Currently, the maximum amount that an individual can receive is USD 33,000 (FEMA, 2017c).

HM usually aggregates 15% of the overall amount of federal assistance under a declaration (FEMA, 2018). It funds projects intended to “prevent or reduce long term risk to life and property from natural hazards” (FEMA, 2011) in accordance with existing FEMA-approved HM plans.

Federal disaster management receives funding through the Disaster Relief Fund (DRF), which is composed of regular annual appropriations by Congress and unspent authority carried over from previous years. FEMA manages the DRF and usually uses it to finance disaster relief for disasters up to a damage level of USD 500 million. In the case of extreme disasters, the president needs to ask Congress to release supplemental appropriations if the DRF is otherwise depleted. Granting supplemental appropriations and regular replenishments of the DRF is the only way that the legislative branch is directly involved in the declaration process (Sylves, 2008, p. 54). Over the years, the largest number of supplemental spending bills have been passed in the event of hurricanes. For a comprehensive overview, see Schroeder (2018).

B Further Theoretical Considerations

Here we show the first-order conditions and solution of the model developed in section 2.2:

$$\begin{aligned}
 \text{FOC's: } \Delta \Phi_j^A &= \Delta \Phi_j^U = 0 \\
 \Leftrightarrow \omega^{-1} &\left(u_i(D_j = 1, s_j) - u_i(D_j = 0, s_j) + \sum_{l=1, l \neq j}^N (1 - 2\theta_l) (u_l(D_j = 1, s_j) - u_l(D_j = 0, s_j)) \right) \\
 &= \omega^{-1} \left((1 - 2\theta) (u_i(D_j = 1, s_j) - u_i(D_j = 0, s_j)) + \sum_{l=1, l \neq j}^N (1 - 2\theta_l) (u_l(D_j = 1, s_j) - u_l(D_j = 0, s_j)) \right) = 0 \\
 \Leftrightarrow u_i(D_j = 1, s_j) - u_i(D_j = 0, s_j) + \dots &= (\mathbf{1} - 2\theta) (u_i(D_j = 1, s_j) - u_i(D_j = 0, s_j)) + \dots = 0 \\
 \Rightarrow s^{*A} &< s^{*U}
 \end{aligned}$$

From $u' > 0$ and $u'' < 0$ it follows that this solution characterizes a global maximum because $\Delta \Phi_j^A(s_j) > \Delta \Phi_j^U(s_j) > 0$ if s_j is large enough.⁴⁰ To further ensure an interior solution with $s^{*A} > 0$ for any $\theta \in (0, 0.5)$, u needs to be sufficiently concave. For extremely high vote leakage (θ close to 0.5), the alignment bias would otherwise result in a corner solution with $s^{*A} = 0$, where the president benefits from channeling resources to aligned counties irrespective of the hurricane strength. However, one can rule out this corner solution without requiring an additional assumption about the curvature of u , by introducing, e.g., voters' fairness concerns (see below).

Fairness Concerns and Public Opinion

As shown by [Alesina & Angeletos \(2005\)](#), societies value redistribution more if they perceive that wealth outcomes are, to a larger extent, determined by luck. Furthermore, experimental and empirical evidence demonstrates that voters consider social and fairness concerns in their preferences for redistributive policies, such as disaster relief ([Bechtel & Mannino, 2019](#); [Durante et al., 2014](#); [Meya et al., 2020](#)). To account for this, we introduce a fairness component $f_i = \alpha \sum_{l=1, l \neq j}^N (D_l \cdot F_i(s_l - \underline{s}) + (1 - D_l) \cdot F_i(\underline{s} - s_l))$, with $F(0) = 0$, $F'_i(s_l) > 0$, and $F''_i(s_l) < 0$, by which voters assess declarations to all other counties. The threshold $\underline{s} > 0$ is the disaster strength above which the electorate starts to support relief provision to another county. Declarations for wind speeds below $\underline{s} > 0$ are electorally punished by the voters. Analogously, the electorate opposes the absence of declarations for $s_l > \underline{s}$. The smaller the difference $s_l - \underline{s}$, the smaller is the potential electoral reward or punishment from voters outside county l . The

⁴⁰An additional assumption for the voter ideology distribution is that ω is sufficiently large so that $\hat{X} \in [-\frac{1}{2}\omega, \frac{1}{2}\omega]$.

parameter $\alpha > 0$ denotes the relative importance of fairness considerations or the strength of the national public opinion.

Adding the fairness component f_i to the voters' reaction functions, Equations (4) and (5) in section 2.2.1 become

$$\hat{X}_i^A = u_i + f_i \geq X_i$$

$$\hat{X}_i^U = (1 - 2\theta)u_i + f_i \geq X_i.$$

Let s^{*A} and s^{*U} with $s^{*A} < s^{*U}$ be the critical wind speeds above which presidents declare disasters to maximize their electoral objective function disregarding fairness considerations. Hence, the FOC's hold with s^{*A} and s^{*U} : $\Delta\Phi_j^A(s^{*A}) = \Delta\Phi_j^U(s^{*U}) = 0$. Including fairness considerations adds an additional factor to the FOC's. From $s^{*A} < s^{*U}$ as well as $F'(s) > 0$ and $F''(s) < 0$ it follows that

$$\Delta\Phi_j^A(s^{*A}) + \sum_{l=1, l \neq j}^N f_l(s^{*A}, \alpha) < \Delta\Phi_j^U(s^{*U}) + \sum_{l=1, l \neq j}^N f_l(s^{*U}, \alpha)$$

$$\Rightarrow s_F^{*A} > s^{*A} \vee s_F^{*U} < s^{*U}$$

$$\Rightarrow s_F^{*U} - s_F^{*A} < s^{*U} - s^{*A}$$

The alignment bias – i.e., the difference between the critical values s_F^{*U} and s_F^{*A} – is thus smaller when fairness considerations are included in the model. Introducing fairness considerations does not entirely eliminate the alignment bias, but it decreases its extent as declarations to weakly hit counties are less beneficial – irrespective of the alignment status in the respective county.

Higher values of α scale up the importance of fairness considerations, so the private utility becomes relatively less important and the difference between s_F^{*U} and s_F^{*A} decreases. The higher α , that is, the higher voters weight the importance of fairness considerations and thereby declaration decisions in other counties relative to their own county and the disutility from higher taxes, the smaller is the difference between s^{*U} and s^{*A} . A stronger public opinion therefore undermines the alignment bias (cf. [Besley & Burgess, 2002](#); [Durante & Zhuravskaya, 2018](#); [Snyder & Strömberg, 2010](#)).

Voter Ideology Distribution

The alignment bias arises because the president is able to shift the cut-point \hat{X}_i^A in aligned counties to a larger extent than \hat{X}_i^U in unaligned counties. However, in reality this might not be the case in all counties since the distribution of voter ideologies determines the amount of votes the president

can swing. If we change the distribution assumption to a single-peaked county-specific ideology distributions with $X_i \in (-\infty; \infty)$ where $\Phi_j(X_i)$ is the respective cumulative distribution function, the president's maximization would still yield an alignment bias if $\Phi^A = \Phi^U$. However, if there are fewer voters with strong ideologies, i.e., the distribution Φ is narrower around the threshold \hat{X} , the potential electoral benefits from a declaration increase, as more voters switch their electoral decision due to a declaration. If competitiveness is much lower in an aligned- compared to a unaligned county, the lower electoral benefits resulting from the lower number of swing voters can outweigh incentives from vote leakage that lead to the alignment bias.

These theoretical considerations explain, why we cannot expect to find the derived sharp binary alignment bias in reality. We rather expect a hump-shaped continuum of positive marginal effects for alignment.

C Hurricanes

Hurricanes constitute the most severe and destructive class of storms.⁴¹ A hurricane is a cyclonically rotating atmospheric low-pressure system with a typical diameter of the order of 600 km, though storms vary considerably regarding their size (Aguado & Burt, 2015, p. 384, Korty, 2013, pp. 481–485). By definition, “hurricanes have sustained wind speeds of 119 km/h or greater” (Aguado & Burt, 2015, p. 383); the most intense hurricanes can contain peak winds of more than 350 km/h (*ibid.*, p. 384).

Hurricanes’ origins are usually cloud clusters forming over the western African coast.⁴² A small fraction of these tropical disturbances encounter conditions that foster the development of an organized rotating low-pressure system (i.e., a tropical depression) that drifts westward over the Atlantic. Essential for hurricane formation are humid conditions and a high water temperature ($>27^{\circ}\text{C}/81^{\circ}\text{F}$) to supply the storm with energy, no air-inversions or strong vertical winds, and a minimum distance from the equator, thus implying a sufficiently strong Coriolis force (Kraus & Ebel, 2003, pp. 156–158; Aguado & Burt, 2015, p. 389). These criteria restrict the development of hurricanes to the marine area $5\text{--}20^{\circ}\text{N}$. If all preconditions are met, a self-intensifying rotating system can emerge, potentially becoming strong enough to be called a tropical storm (wind speeds above 63 km/h) or a hurricane (Kraus & Ebel, 2003, p. 158; Korty, 2013, pp. 481–482). The self-reinforcement stems from the release of latent heat from condensation in the absorbed air, which unleashes even more energy within the clouds, leading to further storm growth as long as conditions remain favorable (Aguado & Burt, 2015, pp. 389–391).

In an established tropical storm, air flows inward to an extreme low-pressure core (the eye). While moving inward, it absorbs latent energy from the warm ocean surface. Closer to the core, condensation and the release of warmth let air rise, which then spirals anticyclonically outward. Some air also slowly sinks within the eye, which is characterized by very low wind speeds. The storm’s highest intensity is within the eyewall, the towering band of clouds 10–20 km from the storm’s center. Moving away from the center, wind speed decreases quickly and steadily (*ibid.*, pp. 385–386; Deryugina, 2017). The strength of a hurricane is generally measured by its maximum sustained surface wind speed (Kraus & Ebel, 2003, pp. 143–145).

Alongside extreme winds, hurricanes produce heavy precipitation. Rainfall within the hurricane is also most intense around the center. However, precipitation does not diminish as steadily when moving outward. The separated bands of clouds spiraling outward can cause heavy rainfall off the

⁴¹As our study deals with tropical cyclones in an American context, we use the term “hurricane,” the conventional expression for storms in the North Atlantic and East Pacific basin. It is a synonym for “tropical cyclone” (Indian Ocean and Australia) and “typhoon” (West Pacific).

⁴²This is true for the majority of storms hitting the U.S. East Coast or the Gulf of Mexico area. Hurricanes also exist in the West Pacific, but most of them move away from land, not affecting the contiguous United States; nevertheless, some make landfall in Mexico and affect the Southwestern United States (Aguado & Burt, 2015, p. 382).

center (Aguado & Burt, 2015, pp. 384–385; Deryugina, 2017; Strobl, 2011). Despite a strong overall correlation of storm strength and total rainfall, Lonfat et al. (2004) report a high asymmetry of hurricane precipitation. Additionally, Konrad et al. (2002) find that local precipitation rates can vary greatly within a single storm. Presumed causes for the vast heterogeneities in rainfall are differences in the speed of movement, the storm’s diameter, and the shape of the crossed area (Knight & Davis, 2009; Konrad et al., 2002). The high degree of heterogeneity in precipitation patterns highlights the importance of using not only wind but also rain data.

Forecasts on the approximate locations of hurricane landfall are only reliable a few days in advance – today, 48 hours before landfall, the average accuracy is 150 km – because of the wildly-erratic nature of hurricane paths (Aguado & Burt, 2015, pp. 404–405). A typical hurricane season spans from June 1 to November 30, with the vast majority of storms occurring between July and October.

D Reported Damage Data – Short Discussion of Criticism in the Literature

The majority of the distributive politics literature evaluates political influence by studying damage outcomes that emerge from endogenous processes. Existing studies on the political economy of disaster relief predominantly use reported damage measures from insurance data or databases such as EM-DAT or SHELDUS. A general criticism is that the measures are not comparable between different types of hazards (Gall et al., 2009). In addition, the construction of the estimates in data sets such as EM-DAT is mostly “based on insurance claims or news stories” (Felbermayr & Gröschl, 2014, p. 92). This can create measurement errors and selection issues. In data sets covering a long time span or many regions, temporal or spatial heterogeneities in the quality of reporting and sources can cause biased estimates (Strobl, 2012).

Analyses of U.S. disaster declarations frequently use loss estimates from the SHELDUS database (e.g., Gasper, 2015; Healy & Malhotra, 2009), which also has its shortcomings. First, only disasters above a threshold of USD 50,000 are included prior to 1995 (Davlasheridze et al., 2017), making the data truncated. Second, SHELDUS covers self-reported data by individual weather stations, which results in a large number of missing observations (see Gallagher, 2019). As Gallagher (2019) explains in his reanalysis of Gasper & Reeves (2011), the usage of SHELDUS in the context of disaster declarations is problematic as one observes many declarations for situations with seemingly no damage according to these data. Third, to obtain county-level estimates, SHELDUS divides state-level losses equally among counties (Davlasheridze et al., 2017; Gasper & Reeves, 2011). Gasper & Reeves (2011) and Healy & Malhotra (2009) attempt to account for this by adopting population weights so that smaller counties are not over-represented. Finally, Gall et al. (2009) detect an inconsistency: estimated total losses from SHELDUS are lower than insured losses reported in other databases.

As explained in the paper, we attempt to overcome these issues by modelling damage directly from meteorological hurricane intensity measures. Our data are complete for our observation period (1965–2018), exogenous, not truncated, and do not suffer from any of the biases listed above.

E Hurricane Data

Wind Speed

To generate a measure for hurricane damages, we adopt the tropical cyclone data assembled by [Kunze \(forthcoming\)](#) with a higher resolution of 1×1 km for the United States. We use data from the International Best Track Archive for Climate Stewardship (IBTrACS), version v03r10, for the years 1965–2018 ([Knapp et al., 2010](#)). This meteorological data set contains all best-track tropical cyclone data collected from weather agencies worldwide. Tropical cyclones are tracked via aviation, buoys, ships, satellites, and weather stations. The resulting data include the wind speed, minimal sea pressure, and location of the center of all tropical cyclones recorded every six hours. To generate spatially varying wind speeds out of the IBTrACS raw data, we run a meteorological wind field model. We consider all wind speed observations above a cutoff of 54 km/h. The code of this model is based on the CLIMADA model from [Aznar-Siguan & Bresch \(2019\)](#) but is adopted to the special needs of the IBTrACS data. It contains the well-established wind field model by [Holland \(1980\)](#), which calculates for each raw data track point

$$S = \begin{cases} \max\left(0, \left(\left(M - \text{abs}(T)\right) * \frac{R^{\frac{3}{2}}}{D} * e^{1-\frac{R}{D}}\right) + T\right), & \text{if } D < 10 * R \text{ from center to outer core} \\ 0, & \text{if } D > 10 * R \text{ out of radius,} \end{cases} \quad (10)$$

where S corresponds to the resulting wind speed. It depends on the maximum sustained wind speed M , the forward speed T , the distance D from the tropical cyclone center, and the maximum wind radius R . The model is restricted to tropical cyclones above a raw data wind speed of 54 km/h and a maximum coastal distance of 500 km. It computes one-hourly asymmetric wind fields at a resolution of 0.01° (approximately 1 km) for every tropical cyclone in our sample. From these calculated wind fields, we take the maximum wind speed per county-year to construct our *Wind Speed* variable. Figure E2 shows the calculated wind fields for Hurricane Matthew hitting the U.S. East Coast in 2016.

Wind speed diminishes with increasing distance from the center (red dotted line) and after landfall. Figure E3 shows the distribution of the *Wind Speed* variable for all hurricanes over the entire sample period. While lower wind speeds are very frequent, catastrophic events are rather rare.

In Panel [b] of Figure JII, we replace our *Wind Speed* damage variable with the damage function proposed by [Emanuel \(2011\)](#). He suggests specific wind speed thresholds above which a certain percentage of physical damage occurs or 50% of the physical infrastructure is destroyed. Consequently, for each

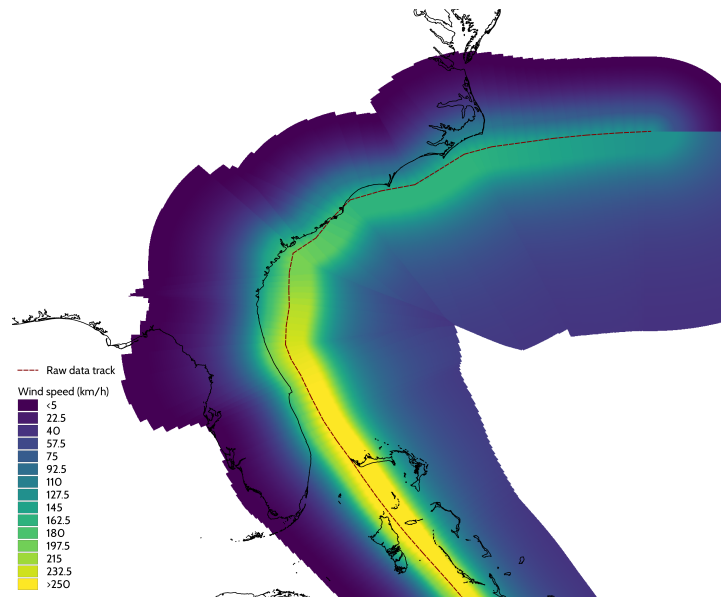


Figure E2: **Wind Field Model and Raw Data Track of Hurricane Matthew, 2016**

The figure displays modeled asymmetric wind fields from our damage model for Hurricane Matthew. The colors indicate wind speed intensities. The red dotted line corresponds to the IBTrACS raw data track.

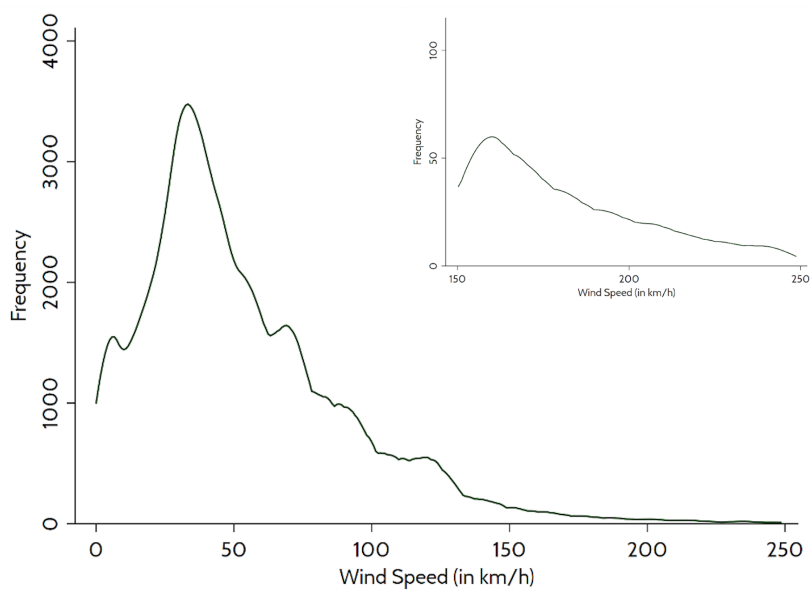


Figure E3: **Distribution of Hurricane *Wind Speed* >0, 1965–2018**

hurricane s in county i , we calculate the following damage index:

$$Damage_{is} = \frac{v_{is}^3}{1 + v_{is}^3}, \quad (11)$$

where

$$v_{is} = \frac{\max[(S_{is} - S_{thresh}), 0]}{S_{half} - S_{thresh}}. \quad (12)$$

S_{is} is the maximum wind speed of storm s in county i as calculated in equation 10. As proposed by Emanuel (2011), we take 93 km/h as the lower-bound damage threshold (S_{thresh}) and 203 km/h as the cutoff where half of the property is destroyed (S_{half}). The resulting damage index ranges from 0 (no damage) to 1 (all buildings destroyed).

Rainfall and Storm Surge

Data on hurricane-related precipitation were provided by Roth (2018) in raw spreadsheet format. These tables report rainfall measures for hurricanes, tropical storms, and tropical depressions from weather stations at geographic locations in North America. We use data from all storms in his data set if they caused rainfall in the contiguous United States.

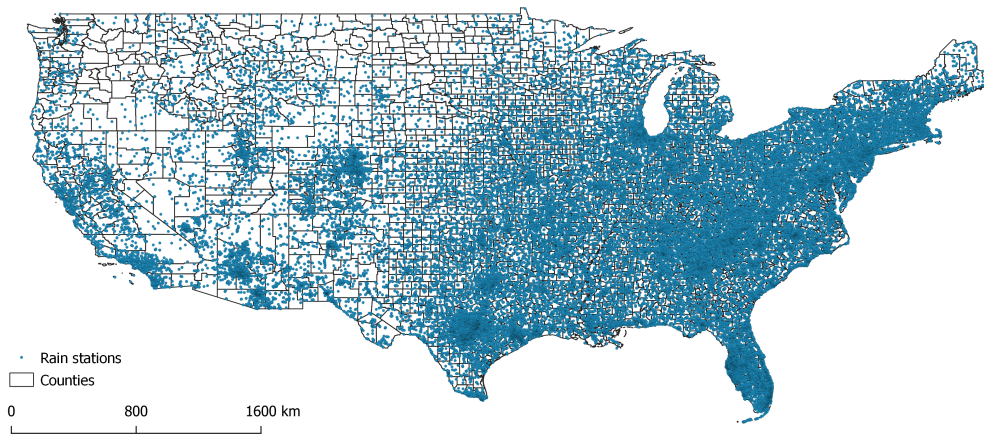


Figure E4: **Distribution of Weather Stations for Hurricane *Rainfall* Data**

As a first step, we calculate total rainfall (in mm) for every storm and every location from the daily records in the data over the entire period of rainfall from the hurricane.⁴³ On a spatial $0.01^\circ \times 0.01^\circ$ grid, we match the data to individual counties. Since flood damage increases with rainfall (Downton & Pielke Jr., 2001), we assume that the strongest rainfall events in a county has the highest likelihood of causing a declaration. We thus keep the strongest precipitation value from each county in each year.

⁴³The data include precipitation that arises from the potential influence of weather fronts interacting with the tropical storm (Czajkowski et al., 2011; Knight & Davis, 2009).

We do not modify the data by interpolating or extrapolating between individual grid points. The degree of spatial interpolation would be an arbitrary choice, and it may lead to biased estimates because local extremes that cause a declaration would potentially be smoothed out from the distribution. As the above map (Figure E4) illustrates, our raw data contain rain stations in almost all counties.

To generate our variable for coastal storm surge damage from hurricanes (*Storm Surge*), we rely on the hydrodynamic model developed by [Kunze & Strobl \(2020\)](#). Within this model, the coastal inundation depth for each tropical cyclone in the IBTrACS [Knapp et al. \(2010\)](#) data set is calculated. The model runs at a spatial resolution of 0.1° and combines inputs from tides, bathymetry, tropical cyclones wind speed, and pressure drop fields in a hydrodynamic simulation using the DELFT3D software. Based on this model, we calculate the maximum inundation depth per county and year.

F Variable Description and Summary Statistics

<i>Declaration</i>	Indicator taking takes the value 1 if a county is assigned at least one federal Emergency Declaration or Major Disaster Declaration in connection to a hurricane in a respective year, and 0 otherwise. All declarations from the categories ‘Hurricane’, ‘Coastal Storm’, ‘Flooding’, and ‘Severe Storm(s)’ in the data provided by FEMA are included if they contain a clear reference to a specific hurricane or tropical storm in their title or could be matched via the date of occurrence to storms in our wind and rain data set. The data exist on the county level since 1965, which restricts our analysis to the time period 1965–2018. Source: OpenFEMA data set: Disaster Declarations Summaries – VI (https://www.fema.gov/openfema , downloaded on October 16, 2017 for declarations until 2015 and on May 20, 2019 for 2016–2018).
<i>Emergency Declaration</i>	Analog to <i>Declaration</i> but restricted to Emergency Declarations.
<i>Major Declaration</i>	Analog to <i>Declaration</i> but restricted to Major Disaster Declarations.
<i>Declarations</i>	Sum of hurricane-related federal Emergency Declarations and Major Disaster Declarations in a county in a given year.
<i>Aligned Governor</i>	Indicator variable that takes the value 1 if governor and president are fellow party members and 0 otherwise. Independent governors are coded as unaligned. The variable captures alignment status as of November, before gubernatorial/presidential elections. Source: Klarner, 2013 (until 2010); for 2011-2018 coded from the National Governors Association; https://www.nga.org .
<i>Aligned Representative</i>	Indicator variable that takes the value 1 if the majority of a county is affiliated with a district that is represented by a politician from the incumbent president’s party in the House of Representatives, and 0 otherwise. District vote results were provided by James M. Snyder. For missing data and corrections, data from the CQ Voting and Elections Collection (https://library.cqpress.com/elections/) and https://ballotpedia.org/ were used.

<i>Aligned Senators</i>	Indicator variable that takes the value 1 if a state is represented by two politicians from the incumbent president's party in the Senate, and 0 otherwise. The variable is coded from Senate election results, obtained from the CQ Voting and Elections Collection.
<i>Alignment Count</i>	A count variable, which represents the number of key politicians (Governor, Senators, and House Representative) that are co-partisans of the president in a respective county. It can thus take the values 0, 1, 2, 3 and 4.
<i>Wind Speed</i>	Maximum wind speed per county and year in km/h. Source: see Appendix E.
<i>Rainfall</i>	Maximum tropical cyclone related rainfall in mm per county and year. Source: Roth, 2018. For further details see Appendix E.
<i>Storm Surge</i>	Maximum storm surge water level in meters per county and year. Source: Kunze & Strobl, 2020.
<i>Wind Speed Count</i>	Variable that counts the number of tropical cyclones with a positive wind speed per county and year.
<i>Rainfall Count</i>	Variable that counts the number of hurricanes that produced positive rainfall in a county in a given year in the data derived from Roth (2018).
<i>Hurricane Month</i>	The month of the strongest tropical cyclone per county and year. Source: see Appendix E.
<i>Mean Annual Rainfall</i>	Mean precipitation per county and year in mm calculated from https://prism.oregonstate.edu/ .
<i>Mean Annual Temperature</i>	Mean temperature per county and year in degree Celsius calculated from https://prism.oregonstate.edu/ .
<i>High-Support District</i>	Indicator variable taking the value 1 if the candidate of the incumbent president's party obtained more than 60% of the vote share in a district in the most recent election and 0 otherwise.
<i>Low-Support District</i>	Indicator variable taking the value 1 if the candidate of the incumbent president's party obtained less than 40% of the vote share in a district in the most recent election, and 0 otherwise.

<i>Presidential Election Year</i>	Indicator variable taking the value 1 in a presidential election year and 0 otherwise.
<i>Any Election Year</i>	Indicator variable taking the value 1 if at least one major election (presidential, congressional, gubernatorial) takes place, and 0 otherwise. Data for gubernatorial election years are provided by Klarner (2013) . Presidential elections are held all 4 years and congressional elections in even years. Missing data for gubernatorial elections were retrieved from ballotpedia.org (last accessed April 1, 2020).
<i>Presidents' First Term</i>	Indicator for presidents' first electoral terms.
<i>Years Pres. Runs for Reelection</i>	Indicator for years in which a president runs for second term.
<i>Electoral Votes</i>	Number of electoral votes of a state in the Electoral College. Source: The American Presidency Project.
<i>County Vote Change (Pres.)</i>	Difference between the vote share of the incumbent president's party in the upcoming and the most recent presidential election. Derived from the data by James M. Snyder and complemented with information from the County Presidential Election Returns 2000-2016 MIT Election Data Science Lab (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ , downloaded March 15, 2019).
<i>Last Term Governor</i>	Indicator for governors that are in their last term due to a constitutional restriction. Source: Klarner (2013) .
<i>Population (log)</i>	Natural logarithm of population per county and year. Source: NBER.
<i>Black Population (log)</i>	Natural logarithm of black population per county and year. Source: https://seer.cancer.gov/popdata/yri1969_2018.19ages/us.1969_2018.19ages.adjusted.exe .
<i>Income (log)</i>	Natural logarithm of income in current 1,000 USD per county and year. Source: U.S. Bureau of Economic Analysis (BEA).
<i>Income per Capita (log)</i>	Per capita income in current USD per county and year. Source: U.S. Bureau of Economic Analysis (BEA).

Table F1: **Summary Statistics**

	Observations	Mean	St. Dev.	Min	Max
<i>Declaration</i>	85,309	0.08	0.27	0.00	1.00
<i>Emergency Declaration</i>	85,309	0.03	0.18	0.00	1.00
<i>Major Declaration</i>	85,309	0.06	0.24	0.00	1.00
<i>Declarations</i>	85,309	0.11	0.41	0.00	5.00
<i>Aligned Governor</i>	85,309	0.46	0.50	0.00	1.00
<i>Aligned Representative</i>	85,309	0.47	0.50	0.00	1.00
<i>Aligned Senators</i>	85,309	0.30	0.46	0.00	1.00
<i>Alignment Count</i>	85,309	1.94	1.25	0.00	4.00
<i>Wind Speed</i>	85,309	24.28	37.37	0.00	352.71
<i>Rainfall</i>	85,309	57.77	67.63	0.00	1,538.73
<i>Storm Surge</i>	85,309	0.04	0.27	0.00	6.01
<i>Wind Speed Count</i>	85,309	0.68	0.96	0.00	7.00
<i>Rainfall Count</i>	85,309	1.86	1.32	0.00	8.00
<i>Hurricane Month</i>	84,947	8.38	1.35	5.00	11.00
<i>Mean Annual Rainfall</i>	85,258	1,132.29	340.87	18.04	3,976.14
<i>Mean Annual Temperature</i>	85,258	14.18	4.16	-0.36	25.83
<i>High-Support District</i>	85,309	0.32	0.47	0.00	1.00
<i>Low-Support District</i>	85,309	0.38	0.49	0.00	1.00
<i>Presidential Election Year</i>	85,309	0.26	0.44	0.00	1.00
<i>Any Election Year</i>	85,309	0.55	0.50	0.00	1.00
<i>Presidents' First Term</i>	85,309	0.66	0.47	0.00	1.00
<i>Years President Runs for Reelection</i>	85,309	0.17	0.38	0.00	1.00
<i>Electoral Votes</i>	85,309	15.01	9.23	3.00	55.00
<i>County Vote Change (Pres.)</i>	81,412	-3.08	12.63	-71.98	88.32
<i>Last Term Governor</i>	71,297	0.41	0.49	0.00	1.00
<i>Population (log)</i>	85,240	10.43	1.31	3.69	16.13
<i>Black Population (log)</i>	79,741	7.24	2.66	0.00	14.17
<i>Income (log)</i>	78,013	17.27	1.98	9.17	24.84
<i>Income per Capita (log)</i>	78,013	13.72	1.25	10.10	16.83

G Robustness – Average Estimation Results for the Alignment Bias

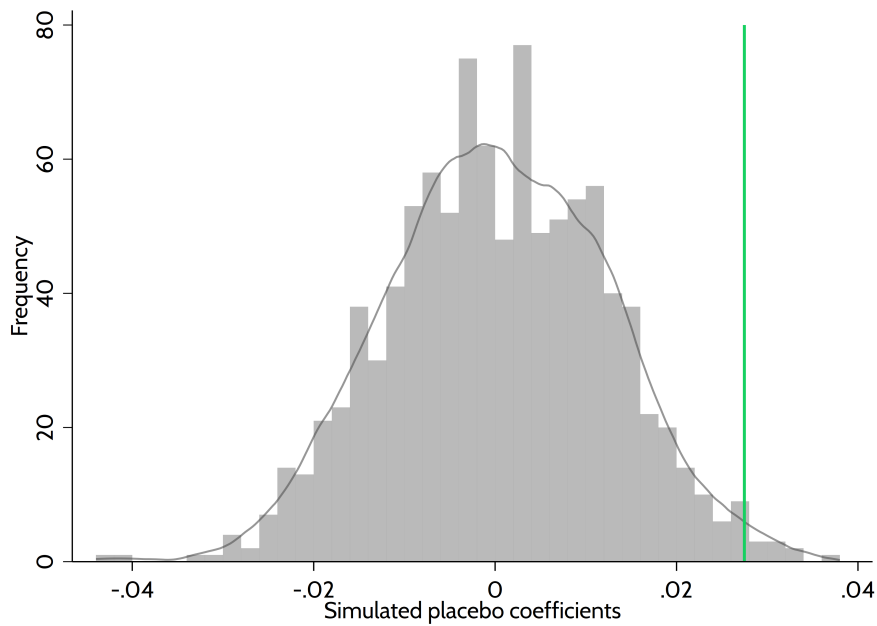


Figure G1: **Randomization Inference (for Average Estimate)**

The figure displays the distribution of simulated coefficients of *Aligned Governor* for 1,000 simulation runs with placebo treatments for the regression in Table 1, column 4. The green bar represents the coefficient using the true data.

Table G1: Robustness – Alternative Clustering

Dep. Var.: Declaration	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Aligned Governor</i>	0.027 (0.002) [0.000]	0.027 (0.002) [0.000]	0.027 (0.010) [0.008]	0.027 (0.014) [0.055]	0.027 (0.011) [0.013]	0.027 (0.014) [0.061]	0.027 (0.009) [0.004]	0.027 (0.011) [0.013]
<i>Aligned Representative</i>	0.010 (0.002) [0.000]	0.010 (0.002) [0.000]	0.010 (0.006) [0.080]	0.010 (0.005) [0.068]	0.010 (0.005) [0.058]	0.012 (0.006) [0.030]	0.011 (0.005) [0.036]	0.011 (0.005) [0.041]
<i>Aligned Senators</i>	0.024 (0.002) [0.000]	0.024 (0.002) [0.000]	0.024 (0.014) [0.087]	0.024 (0.015) [0.128]	0.024 (0.014) [0.097]	0.026 (0.015) [0.070]	0.023 (0.012) [0.056]	0.023 (0.013) [0.072]
<i>Wind Speed (St. Dev.)</i>	0.074 (0.002) [0.000]	0.074 (0.002) [0.000]	0.074 (0.006) [0.000]	0.074 (0.010) [0.000]	0.074 (0.008) [0.000]	0.075 (0.010) [0.000]	0.074 (0.007) [0.000]	0.074 (0.009) [0.000]
<i>Rainfall (St. Dev.)</i>	0.069 (0.002) [0.000]	0.069 (0.001) [0.000]	0.069 (0.008) [0.000]	0.069 (0.007) [0.000]	0.069 (0.005) [0.000]	0.072 (0.006) [0.000]	0.070 (0.005) [0.000]	0.070 (0.006) [0.000]
<i>Storm Surge (St. Dev.)</i>	0.030 (0.006) [0.000]	0.030 (0.005) [0.000]	0.030 (0.010) [0.004]	0.030 (0.011) [0.007]	0.030 (0.009) [0.001]	0.031 (0.011) [0.003]	0.029 (0.009) [0.001]	0.029 (0.010) [0.003]
Cluster	County	County & Year	State	Year	State x Year	Spatial	Hurricane x State	Hurricane
Observations	85,309	85,309	85,309	85,309	85,309	85,309	83,084	83,084

The table displays regression coefficients with different clustered standard errors in parentheses for the estimation in column 4 in the main results table. *p*-values are shown in brackets. All estimations use the linear fixed effect-within estimator and include county and year fixed effects. *Wind Speed*, *Rainfall*, and *Storm Surge* are shown in standard deviation increases (above zero). Standard deviations for *Wind Speed*, *Rainfall*, and *Storm Surge* are 38.78 km/h, 68.17 mm, and 0.8 m, respectively. Models 1-5 and 7-8 include county-specific linear time trends. Model 6 includes a HAC arbitrary spatio-temporal clustering with a radius of 1000 km and a 10 year cutoff. The sample runs from 1965–2018 in all regressions.

Table G2: **Average Regression Results – Past Influences**

Dep. Var.: <i>Declaration</i>	(1)	(2)
<i>Aligned Governor</i>	0.029 (0.011) [0.006]	0.027 (0.011) [0.012]
<i>Aligned Representative</i>	0.010 (0.005) [0.055]	0.011 (0.005) [0.040]
<i>Aligned Senators</i>	0.022 (0.013) [0.104]	0.025 (0.014) [0.075]
<i>Wind Speed (St. Dev.)</i>	0.073 (0.007) [0.000]	0.074 (0.008) [0.000]
<i>Rainfall (St. Dev.)</i>	0.067 (0.005) [0.000]	0.069 (0.005) [0.000]
<i>Storm Surge (St. Dev.)</i>	0.031 (0.009) [0.001]	0.030 (0.009) [0.002]
Lags	<i>Declaration</i>	<i>Wind Speed</i>
Observations	85,309	85,309

The table displays regression coefficients with two-way clustered standard errors on the state \times year and county level in parentheses. p -values are shown in brackets. All estimations use the linear fixed effect-within estimator and include county and year fixed effects as well as county-specific linear time trends. The regression model in column (1) includes 10 lags of the *Declaration* variable, and the model in column (2) includes 10 lags of *Wind Speed*. *Wind Speed*, *Rainfall*, and *Storm Surge* are shown in standard deviation increases (above zero). Standard deviations for *Wind Speed*, *Rainfall*, and *Storm Surge* are 38.78 km/h, 68.17 mm, and 0.8 m, respectively. The sample runs from 1965–2018 in all regressions.

Table G3: Robustness – Alternative Models

Dep. Var.: <i>Declaration(s)</i>	(1)	(2)	(3)	(4)
<i>Aligned Governor</i>	0.607 (0.043) [0.000]	0.301 (0.023) [0.000]	0.385 (0.023) [0.000]	0.385 (0.135) [0.004]
<i>Aligned Representative</i>	0.159 (0.040) [0.000]	0.083 (0.021) [0.000]	0.109 (0.026) [0.000]	0.109 (0.060) [0.072]
<i>Aligned Senators</i>	0.498 (0.044) [0.000]	0.246 (0.024) [0.000]	0.339 (0.029) [0.000]	0.339 (0.171) [0.048]
<i>Wind Speed (St. Dev.)</i>	0.926 (0.021) [0.000]	0.489 (0.011) [0.000]	0.452 (0.015) [0.000]	0.452 (0.043) [0.000]
<i>Rainfall (St. Dev.)</i>	0.765 (0.018) [0.000]	0.413 (0.009) [0.000]	0.204 (0.013) [0.000]	0.204 (0.031) [0.000]
<i>Storm Surge (St. Dev.)</i>	0.092 (0.083) [0.264]	0.034 (0.043) [0.429]	-0.089 (0.043) [0.037]	-0.089 (0.046) [0.056]
Model	logit	probit	Poisson	PPML
Observations	64,579	64,579	68,616	64,579

The table displays regression coefficients for different estimation models with SE in parentheses. *p*-values are shown in brackets. Conditional FE logit and probit estimations are computed using the Stata package written by Fernández-Val & Weidner (2016). For the Poisson pseudo-maximum likelihood (PPML) estimation, we use the package developed by Correia et al. (2020). In the logit and probit model, the dependent variable is *Declaration*, whereas for the remaining models it is *Declarations*. All models include county and year fixed effects. *Wind Speed*, *Rainfall*, and *Storm Surge* are shown in standard deviation increases (above zero). Standard deviations for *Wind Speed*, *Rainfall*, and *Storm Surge* are 38.78 km/h, 68.17 mm, and 0.8 m, respectively. The sample runs from 1965–2018 in all regressions.

Table G4: **Robustness – Socioeconomic Control Variables**

Dep. Var.: <i>Declaration</i>	(1)	(2)	(3)	(4)	(5)	(6)
<i>Aligned Governor</i>		0.032 (0.012) [0.006]	0.027 (0.011) [0.020]	0.027 (0.011) [0.013]	0.026 (0.011) [0.014]	0.026 (0.011) [0.015]
<i>Aligned Representative</i>			0.011 (0.005) [0.024]	0.009 (0.005) [0.078]	0.009 (0.005) [0.078]	0.009 (0.005) [0.070]
<i>Aligned Senators</i>			0.026 (0.013) [0.049]	0.023 (0.014) [0.104]	0.026 (0.014) [0.070]	0.025 (0.014) [0.076]
<i>Population (log)_{t-1}</i>	0.010 (0.004) [0.019]	0.011 (0.005) [0.017]	0.012 (0.005) [0.011]	-0.003 (0.004) [0.348]	-0.003 (0.003) [0.291]	-0.004 (0.003) [0.204]
<i>Black Population (log)_{t-1}</i>	-0.007 (0.002) [0.004]	-0.007 (0.002) [0.008]	-0.005 (0.002) [0.028]	-0.007 (0.003) [0.009]	-0.007 (0.003) [0.009]	-0.007 (0.003) [0.009]
<i>Real Income (log)_{t-1}</i>	0.014 (0.006) [0.014]	0.012 (0.006) [0.041]	0.010 (0.006) [0.108]	0.008 (0.007) [0.281]	0.008 (0.007) [0.252]	0.009 (0.007) [0.209]
<i>Per Capita Real Income (log)_{t-1}</i>	-0.019 (0.009) [0.037]	-0.017 (0.009) [0.064]	-0.014 (0.009) [0.135]	-0.009 (0.009) [0.336]	-0.010 (0.009) [0.267]	-0.011 (0.009) [0.222]
<i>Wind Speed (St. Dev.)</i>	0.075 (0.008) [0.000]	0.075 (0.007) [0.000]	0.075 (0.007) [0.000]	0.074 (0.007) [0.000]		
<i>Rainfall (St. Dev.)</i>	0.072 (0.005) [0.000]	0.072 (0.005) [0.000]	0.071 (0.005) [0.000]	0.069 (0.005) [0.000]	0.069 (0.005) [0.000]	0.069 (0.005) [0.000]
<i>Storm Surge (St. Dev.)</i>	0.032 (0.010) [0.001]	0.031 (0.010) [0.001]	0.031 (0.010) [0.001]	0.030 (0.010) [0.002]	-0.002 (0.009) [0.813]	-0.002 (0.009) [0.797]
Time Trends				X	X	X
Wind Speed Polynomials					X	
Wind Speed Bins						X
Observations	85,309	85,309	85,309	85,309	85,309	85,309

The table displays regression coefficients with two-way clustered standard errors on the state \times year and county level in parentheses. p -values are shown in brackets. All estimations use the linear fixed effect-within estimator and include county and year fixed effects. *Wind Speed*, *Rainfall*, and *Storm Surge* are shown in standard deviation increases (above zero). Standard deviations for *Wind Speed*, *Rainfall*, and *Storm Surge* are 38.78 km/h, 68.17 mm, and 0.8 m, respectively. Models 4-6 include county-specific linear time trends. ‘Wind Speed Bins’ signifies the usage of the semi-parametric approach to model wind speed. ‘Wind Speed Polynomials’ indicates the usage of quartic polynomials. The sample runs from 1965–2018 in all regressions.

H Main Results – Detailed Regression Output Tables for Figure 3

Table H1: **Polynomial Regression Results of Main Specification**

Dep. Var.: <i>Declaration</i>	(1)
<i>Wind Speed</i>	0.0008 (0.0009) [0.3902]
<i>Wind Speed</i> ²	-1.84 · 10 ⁻⁵ (1.94 · 10 ⁻⁵) [0.3445]
<i>Wind Speed</i> ³	2.58 · 10 ⁻⁷ (1.17 · 10 ⁻⁷) [0.0280]
<i>Wind Speed</i> ⁴	-5.71 · 10 ⁻¹⁰ (2.06 · 10 ⁻¹⁰) [0.0056]
<i>Rainfall</i>	0.0010 (0.0001) [0.0000]
<i>Storm Surge</i>	-0.0030 (0.0105) [0.7777]
<i>Aligned Governor</i>	0.0033 (0.0087) [0.7067]
<i>Aligned Governor</i> × <i>Wind Speed</i>	-0.0016 (0.0012) [0.1730]
<i>Aligned Governor</i> × <i>Wind Speed</i> ²	6.52 · 10 ⁻⁵ (2.70 · 10 ⁻⁷) [0.0161]
<i>Aligned Governor</i> × <i>Wind Speed</i> ³	-3.90 · 10 ⁻⁷ (1.76 · 10 ⁻⁷) [0.0263]
<i>Aligned Governor</i> × <i>Wind Speed</i> ⁴	6.00 · 10 ⁻¹⁰ (3.31 · 10 ⁻¹⁰) [0.0701]
<i>Aligned Representative</i>	0.0093 (0.0052) [0.0741]
<i>Aligned Senators</i>	0.0258 (0.0138) [0.0628]
Time Trends	X
Observations	85,309

The table displays regression coefficients of the main polynomial specification with two-way clustered standard errors on the state × year and county level in parentheses. *p*-values are shown in brackets. All estimations use the linear fixed effect-within estimator and include county and year fixed effects. The sample runs from 1965–2018 in all regressions.

Table H2: **Bins Regression Results of Main Specification**

Dep. Var.: Declaration	(t)
<i>Wind Speed Bin 1</i>	0.0052 (0.0191) [0.7848]
<i>Wind Speed Bin 2</i>	0.0179 (0.0140) [0.1999]
<i>Wind Speed Bin 3</i>	0.0292 (0.0210) [0.1642]
<i>Wind Speed Bin 4</i>	0.0757 (0.0233) [0.0012]
<i>Wind Speed Bin 5</i>	0.1088 (0.0432) [0.0119]
<i>Wind Speed Bin 6</i>	0.1732 (0.0639) [0.0068]
<i>Wind Speed Bin 7</i>	0.4687 (0.0628) [0.0000]
<i>Wind Speed Bin 8</i>	0.5879 (0.0742) [0.0000]
<i>Wind Speed Bin 9</i>	0.5219 (0.1026) [0.0000]
<i>Wind Speed Bin 10</i>	0.7337 (0.0584) [0.0000]
<i>Rainfall</i>	0.0010 (0.0001) [0.0000]
<i>Storm Surge</i>	-0.0032 (0.0104) [0.7583]
<i>Aligned Governor</i>	0.0032 (0.0083) [0.6973]
<i>Aligned Governor × Wind Speed Bin 1</i>	-0.0031 (0.0268) [0.9069]
<i>Aligned Governor × Wind Speed Bin 2</i>	0.0012 (0.0197) [0.9517]
<i>Aligned Governor × Wind Speed Bin 3</i>	0.0838 (0.0379) [0.0271]
<i>Aligned Governor × Wind Speed Bin 4</i>	0.1023 (0.0353) [0.0038]
<i>Aligned Governor × Wind Speed Bin 5</i>	0.1833 (0.0523) [0.0005]
<i>Aligned Governor × Wind Speed Bin 6</i>	0.2360 (0.0760) [0.0019]
<i>Aligned Governor × Wind Speed Bin 7</i>	0.1137 (0.0813) [0.1620]
<i>Aligned Governor × Wind Speed Bin 8</i>	0.0670 (0.1038) [0.5186]
<i>Aligned Governor × Wind Speed Bin 9</i>	0.1910 (0.1103) [0.0835]
<i>Aligned Governor × Wind Speed Bin 10</i>	-0.0338 (0.0764) [0.6578]
<i>Aligned Senators</i>	0.0252 (0.0137) [0.0661]
<i>Aligned Representative</i>	0.0096 (0.0051) [0.0622]
Time Trends	X
Observations	85,309

The table displays regression coefficients of the main bin specification with two-way clustered standard errors on the state × year and county level in parentheses. *p*-values are shown in brackets. All estimations use the linear fixed effect-within estimator and include county and year fixed effects. The sample runs from 1965–2018 in all regressions.

Table H₃: **Sequential *F*-Tests Polynomials**

	<i>F</i> -statistic	<i>p</i> -value
9 vs 8	0.411	0.663
8 vs 7	1.177	0.308
7 vs 6	1.098	0.334
6 vs 5	0.997	0.369
5 vs 4	0.507	0.603
4 vs 3	3.843	0.022
3 vs 2	15.351	0.000

The table displays the results of seven *F*-tests based on our polynomial regression model presented in the paper. We test the unrestricted model of polynomial degree n against its restricted alternative with degree $n - 1$ as depicted in the leftmost column. Each restriction consists of two coefficients, the excluded *Wind Speed*-polynomial and its interaction with *Aligned Governor*. *p*-values document which restrictions are associated with a significantly better fit to explain the variation in the dependent variable *Declaration*.

J Heterogeneous Alignment Bias – Robustness and Further Results

J.1 Standard Errors and Randomization Inference

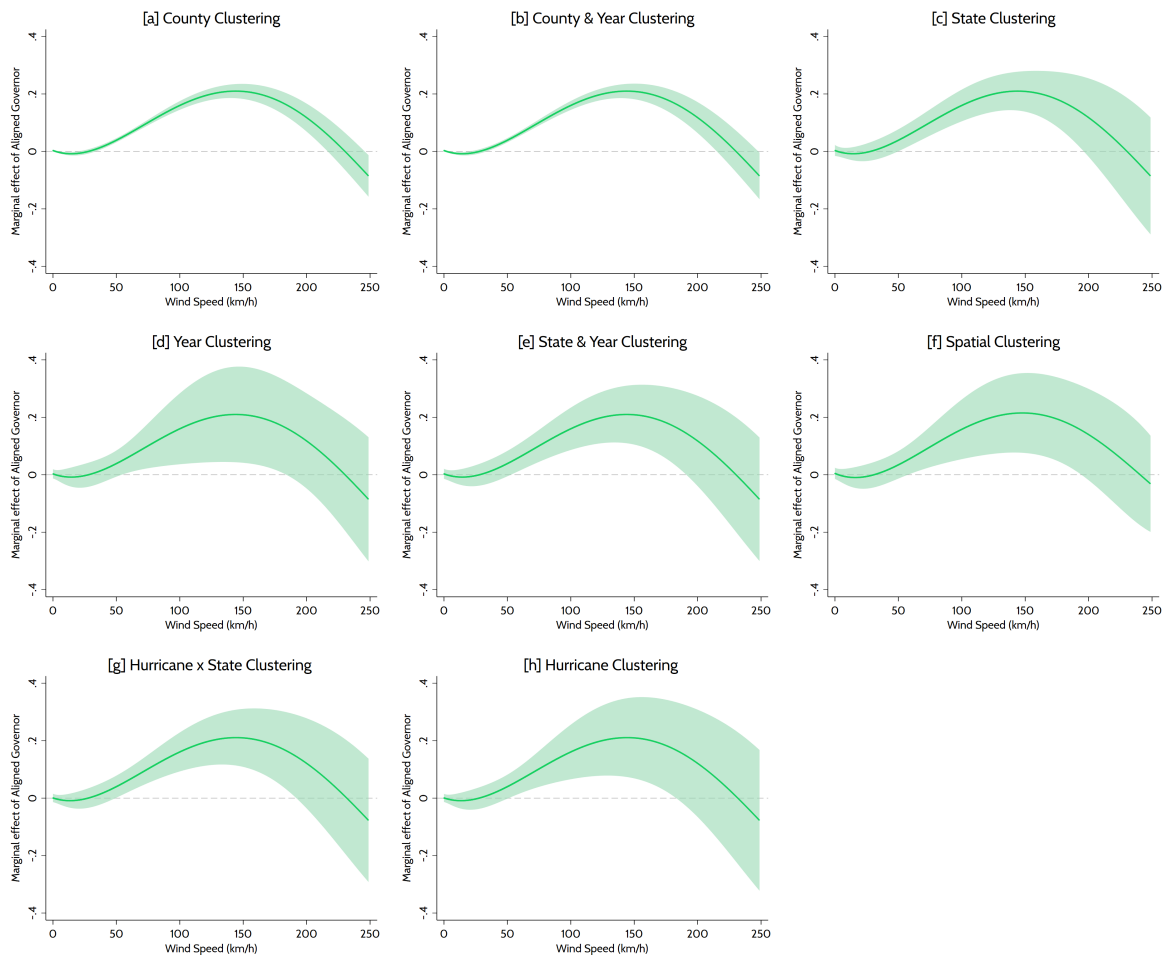


Figure J1: **Robustness to Alternative Clustering Choices**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying the alternative clustering levels as indicated in the panel titles. Panel [f] applies a HAC arbitrary spatio-temporal clustering with a radius of 1,000 km and a 10 year cut-off. The sample covers county-year observations from 1965–2018.

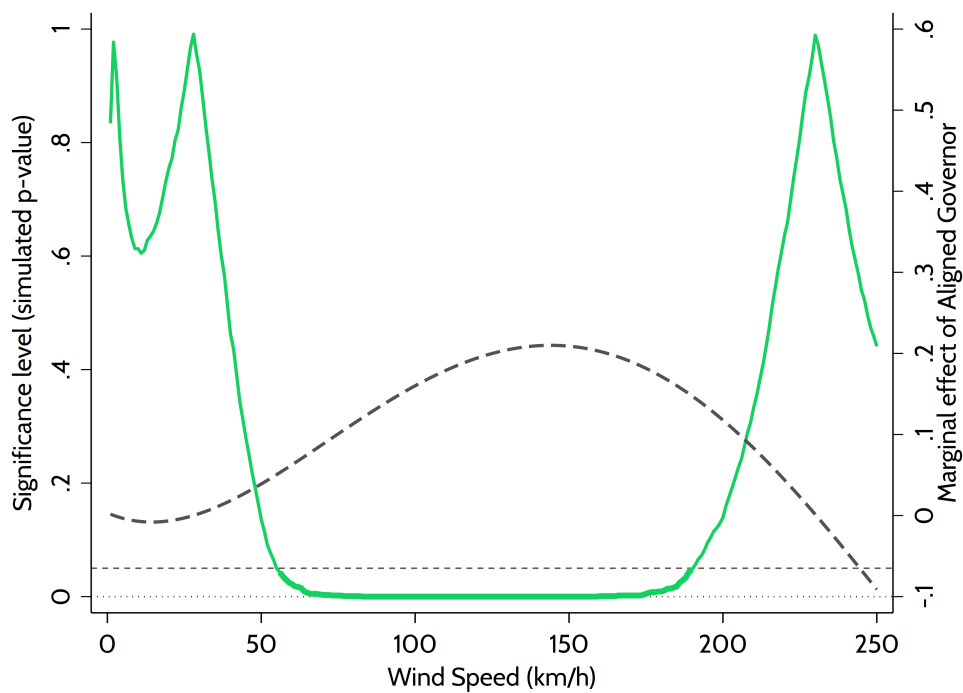


Figure J2: **Randomization Inference: Simulated P-Value**

The figure displays the permutation p -value ($p_{perm.} = N^{-1} \sum_{i=i}^N \mathbb{1}[|\beta| < |\beta_{i,placebo}|]$) of the marginal effect of *Aligned Governor* for every *Wind Speed* in green, in bold print for the interval significant at the 95% confidence level derived from the simulation displayed in the paper. The gray dashed line represents the coefficient size using the true data.

J.2 Subsamples

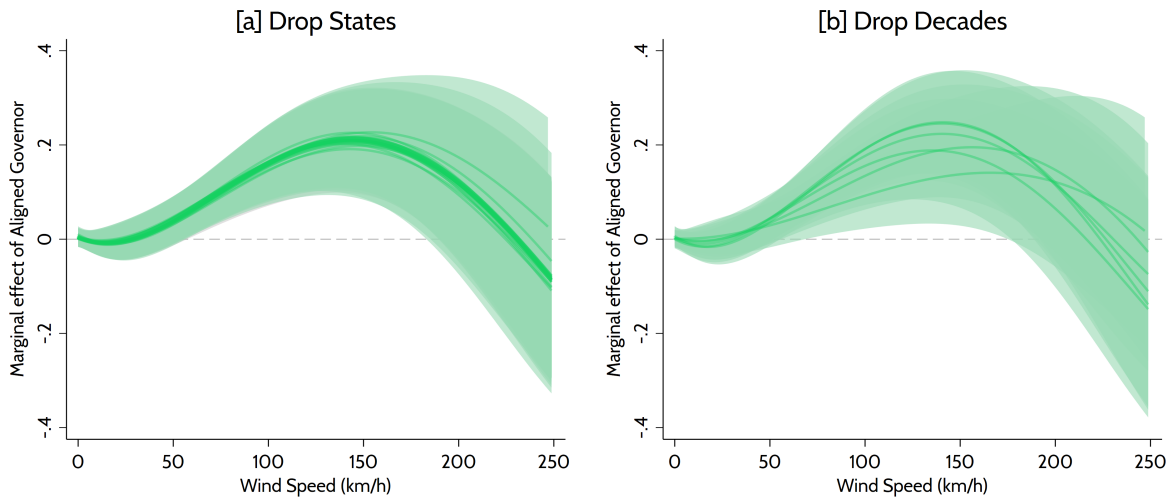


Figure J3: **Robustness: Omitting States and Decades**

This figure shows the sensitivity of our result to the omission of groups of observations. It displays marginal effects of *Aligned Governor* from individual regressions, where each regression omits all observations from one state [a] or decade [b]. The panels show separate lines for the predicted marginal effects from each regression. The transparent shaded areas indicate the respective 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level.

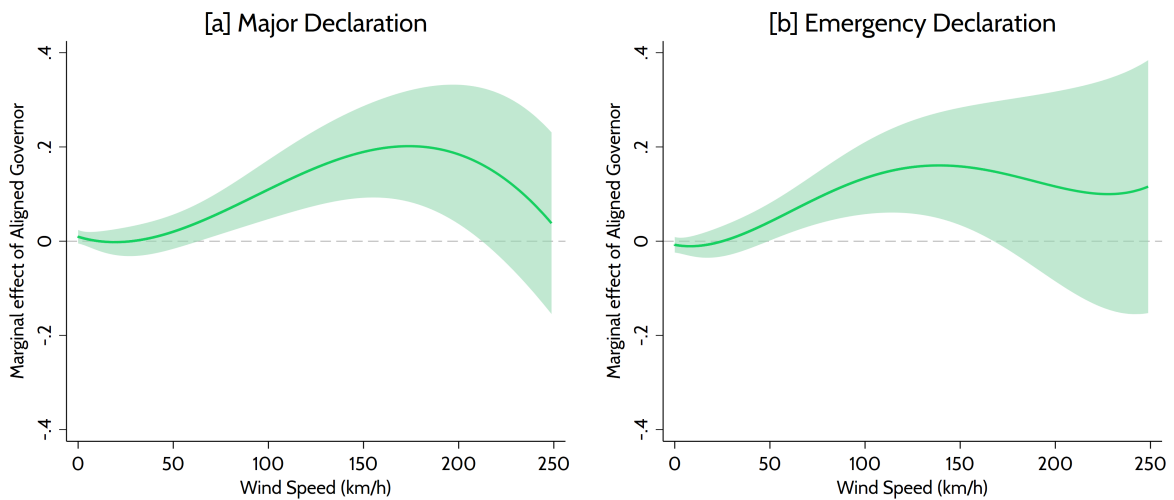


Figure J4: **Major Disaster Declarations and Emergency Declarations**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. In Panel [a], the dependent variable is *Major Declaration* and in Panel [b] *Emergency Declaration*.

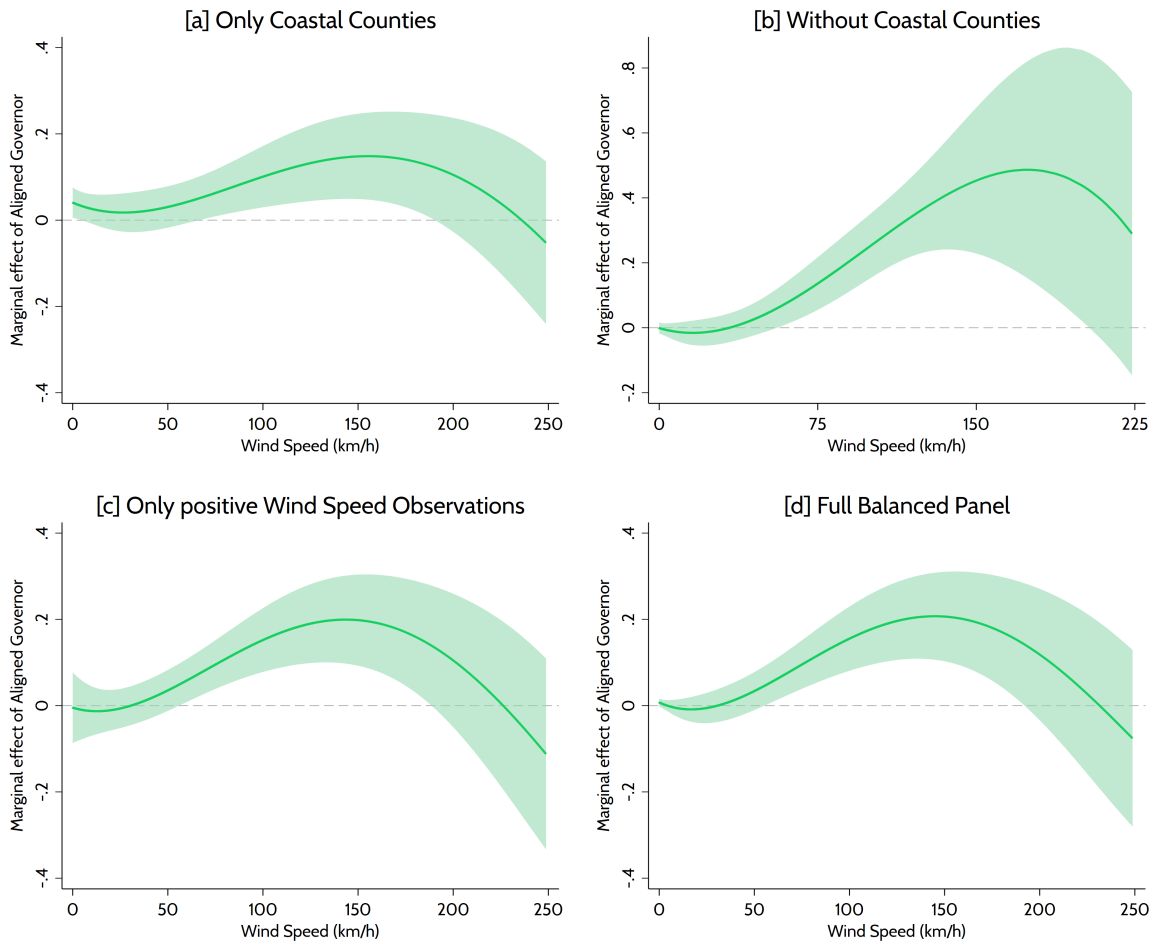


Figure J5: **Sensitivity: Subsamples**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. Panel [a] uses a subsample of coastal counties and Panel [b] non-coastal counties. Panel [c] includes only observations with a positive *Wind Speed* observation. Panel [d] uses a full balanced panel, including observations with both zero *Wind Speed* and *Rainfall*.

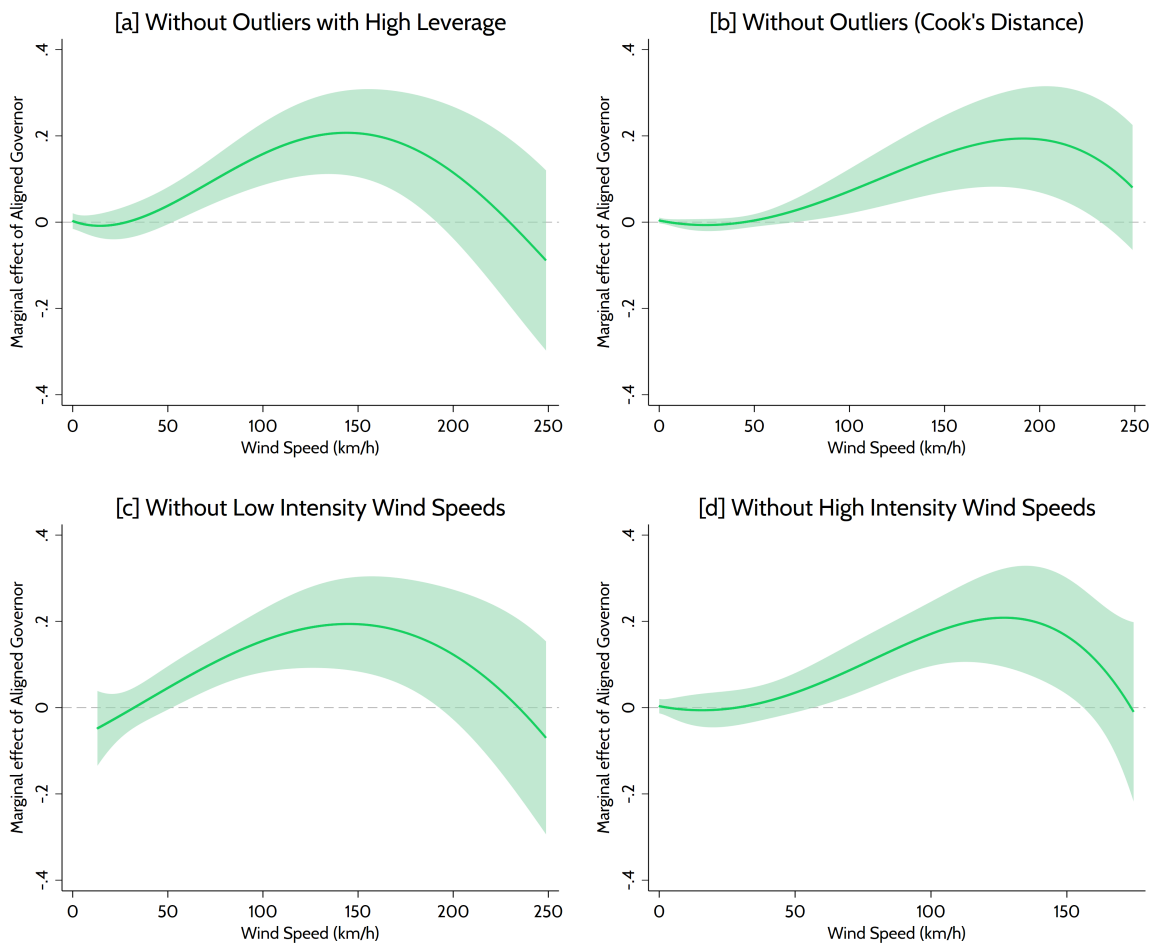


Figure J6: **Robustness: Excluding Outliers**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. Panel [a] excludes all observations with wind speeds below the 10% percentile (13 km/h). Panel [b] excludes all observations with wind speeds above the 99% percentile (183 km/h). Panel [c] excludes all observations above a leverage of $(2k + 2)/n$. Panel [d] excludes all observations with a higher Cook’s distance measure of $4/n$.

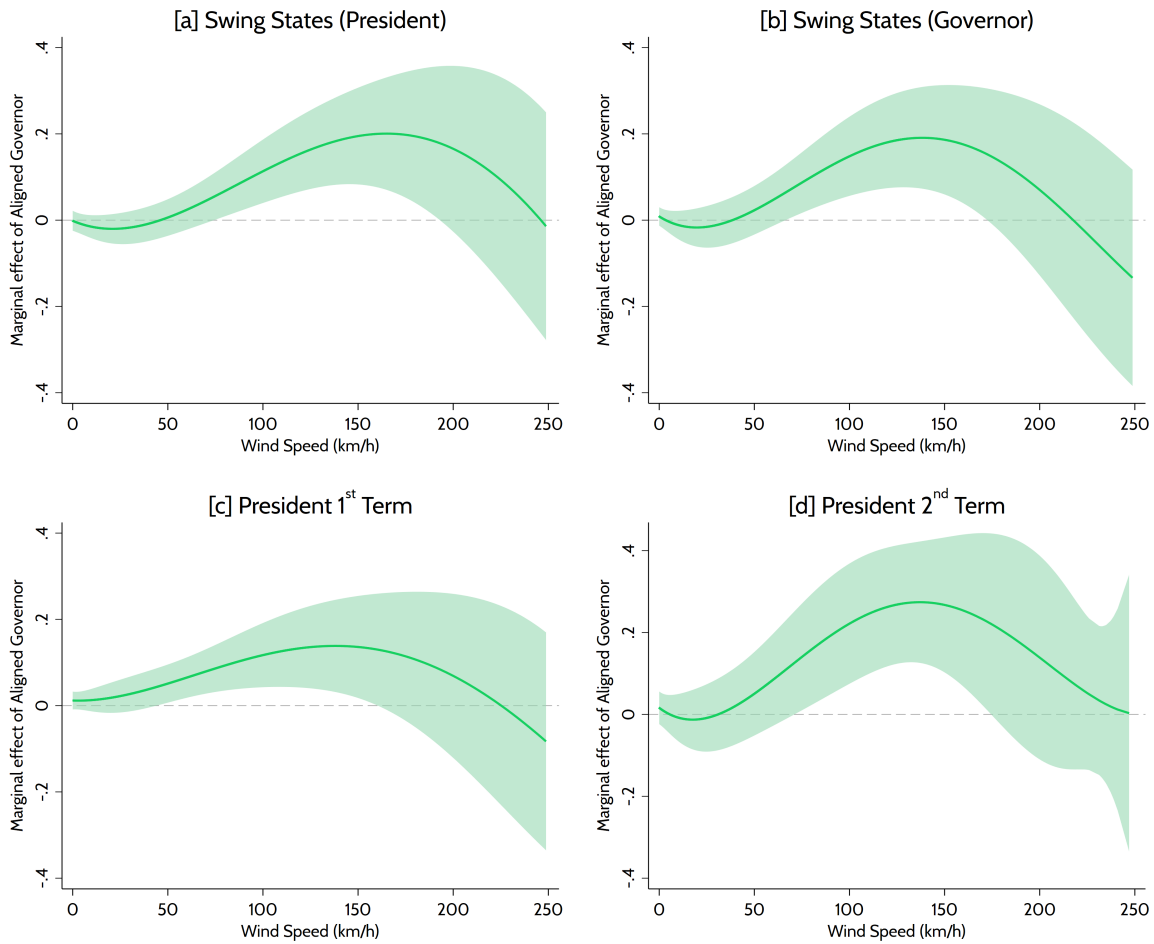


Figure J7: Swing States and Different Terms of the Presidents

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. Panel [a] restricts the sample to swing states in terms of the presidential election (all observations in which the statewide majority shifted at least once in the last three elections). Panel [b] restricts the sample to swing states in terms of the gubernatorial election (all observations in which the statewide majority shifted at least once in the last three elections). Panel [c] shows the results for presidents in their first term and Panel [d] for their second term.

J.3 Alternative Specifications and Triple Interactions

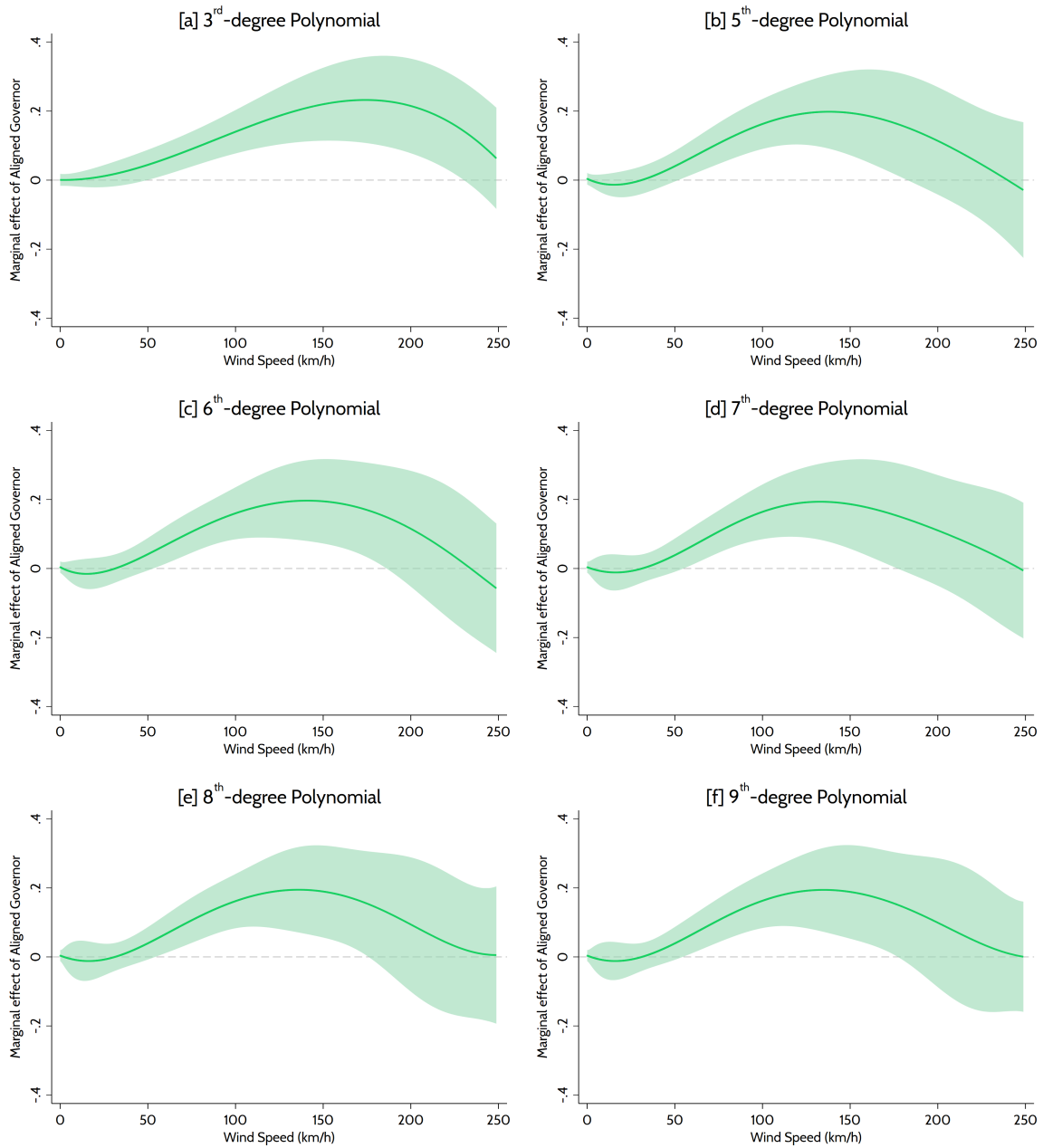


Figure J8: **Robustness: Higher *Wind Speed* Polynomials**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. Panels [a]–[f] apply a *Wind Speed* polynomial with different polynomial degrees.

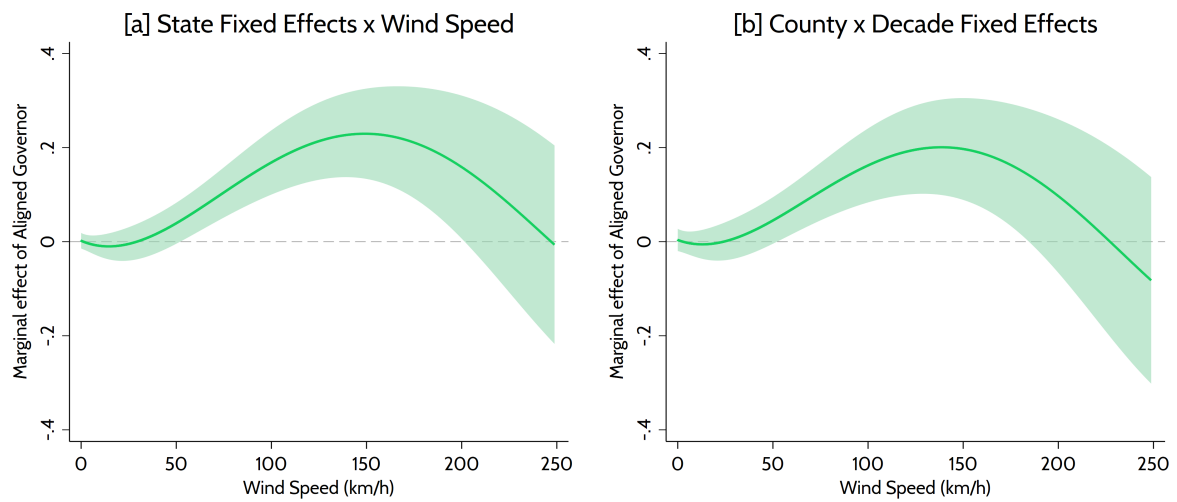


Figure J9: Robustness: County \times Decade Fixed Effects & State-Specific Wind Speed Controls

This figure shows the sensitivity of our main result to more flexible estimation models. The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed* (solid green line). The light green shaded area represents 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. Panel [a] adds separate linear *Wind Speed* effects for each state added to our polynomial estimation. Panel [b] includes county \times decade fixed effects in our polynomial estimation.

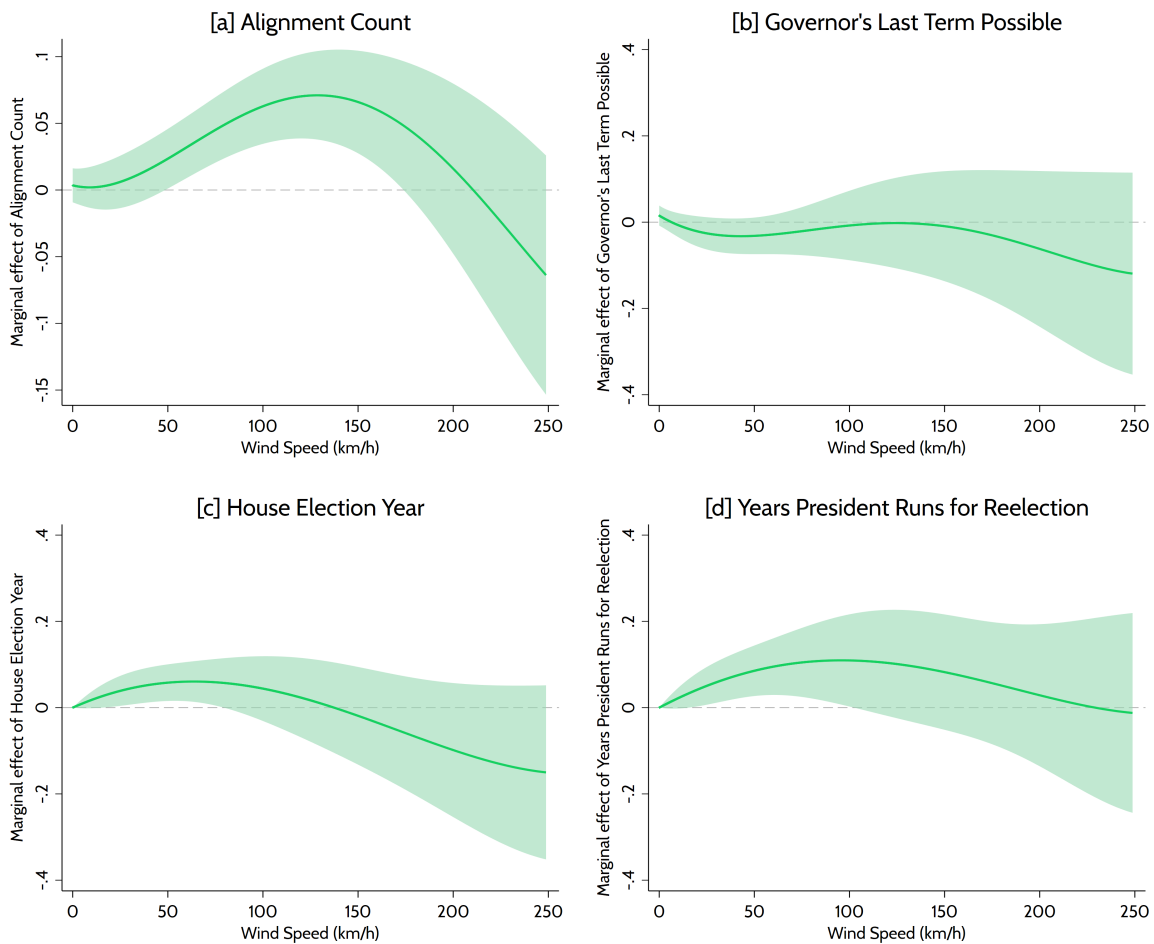


Figure J10: **Additional Specifications and Further Political Factors**

The figure displays marginal effects for the variables of interest depicted on the vertical axes from four polynomial regressions. The shaded areas represent 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. In Panel [a], *Alignment Count* is a variable that indicates how many of the major politicians (governor, senators, representative) are aligned with the president. In Panel [b], *Governor's Last Term Possible* is an indicator taking the value 1 if governors are in their last term due to a constitutional restriction that prohibits them to run for the office again. Panel [c] includes an indicator for congressional election years. Panel [d] interacts an indicator for years in which an incumbent president runs for reelection with the *Wind Speed* polynomial.

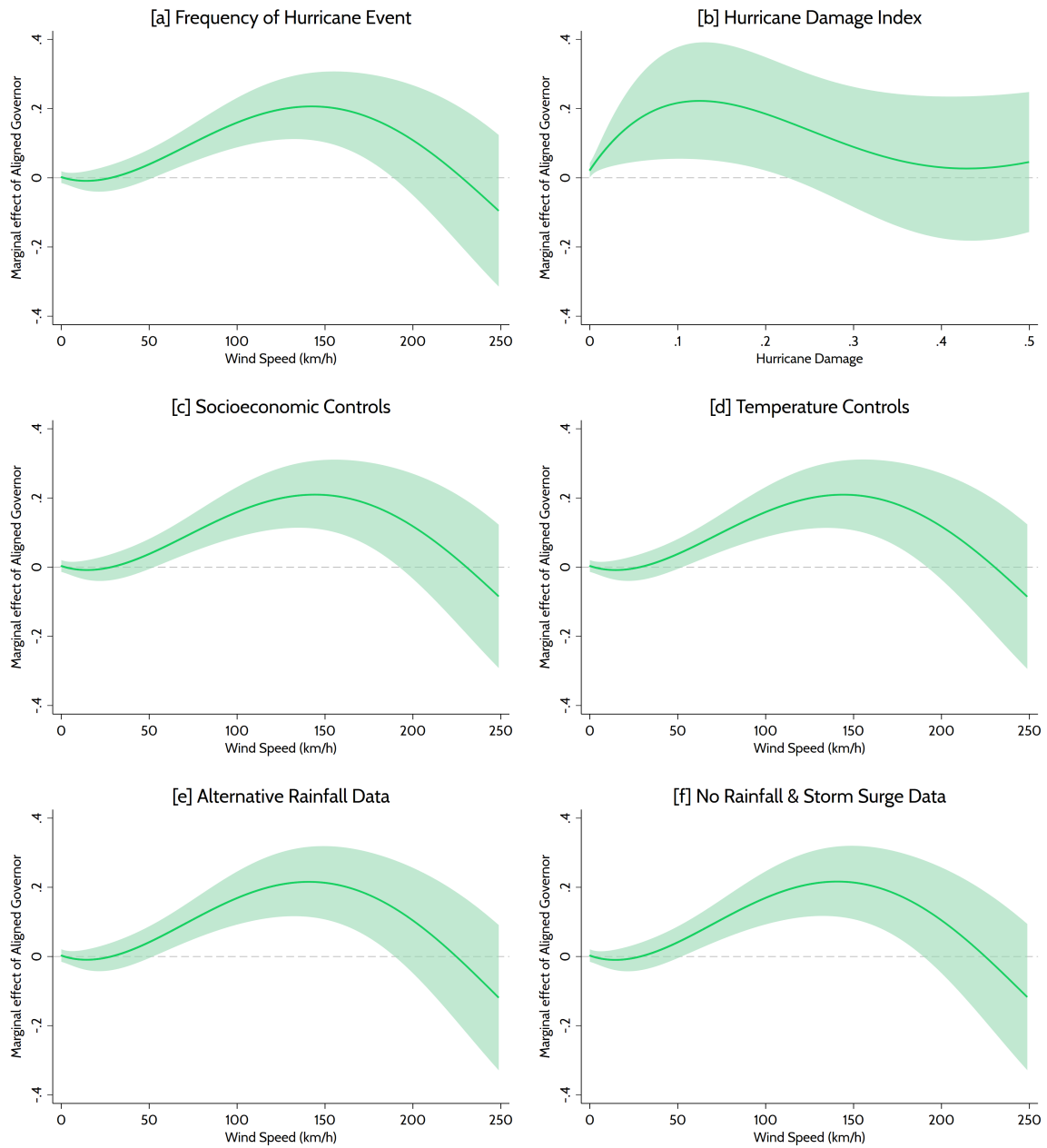


Figure JII: **Robustness: Alternative Specifications**

This figure shows the robustness of our main result to alternative specifications. The panels display marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. Panel [a] includes two variables that account for the frequency of *Wind Speed* and *Rainfall* incidences respectively. Panel [b] includes the wind speed damage index as proposed by Emanuel (2011) instead of our *Wind Speed* measure. The alignment bias is significant for wind speeds between 93 km/h and 165 km/h (damage index = 0.22). In Panel [c] the estimation includes *Population (log)*, *Black Population (log)*, *Income (log)*, *Income Per Capita (log)*, all lagged by one year. Panel [d] includes additional temperature controls (*Mean Annual Temperature*) from the Prism data base. Panel [e] uses alternative rainfall data (*Mean Annual Rainfall*) from the Prism data base. Panel [f] omits the *Rainfall*- and *Storm Surge*-controls.

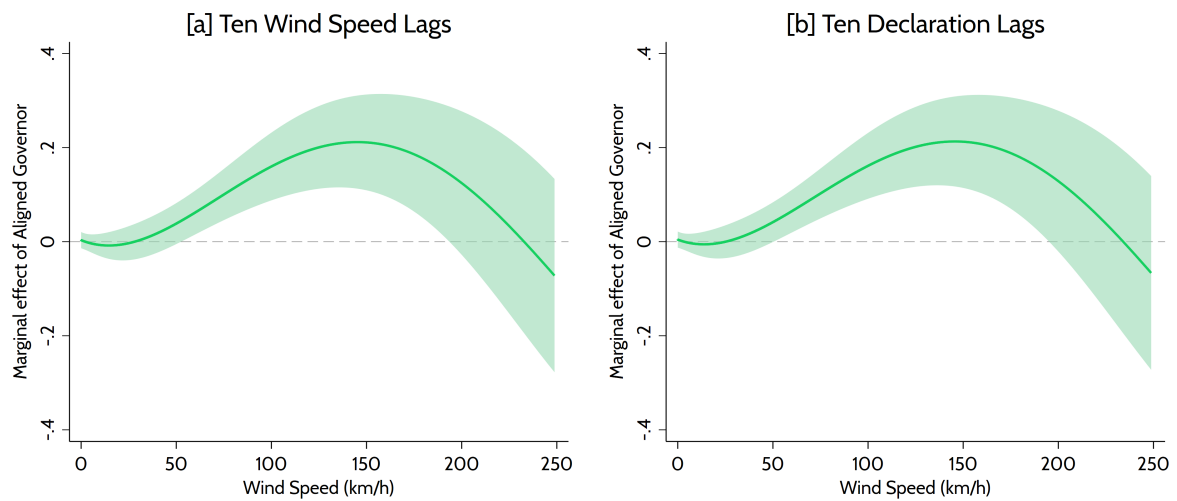


Figure J12: **Robustness: Lags**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. Panel [a] adds the first ten lags of *Wind Speed* and Panel [b] the first ten lags of *Declaration*.

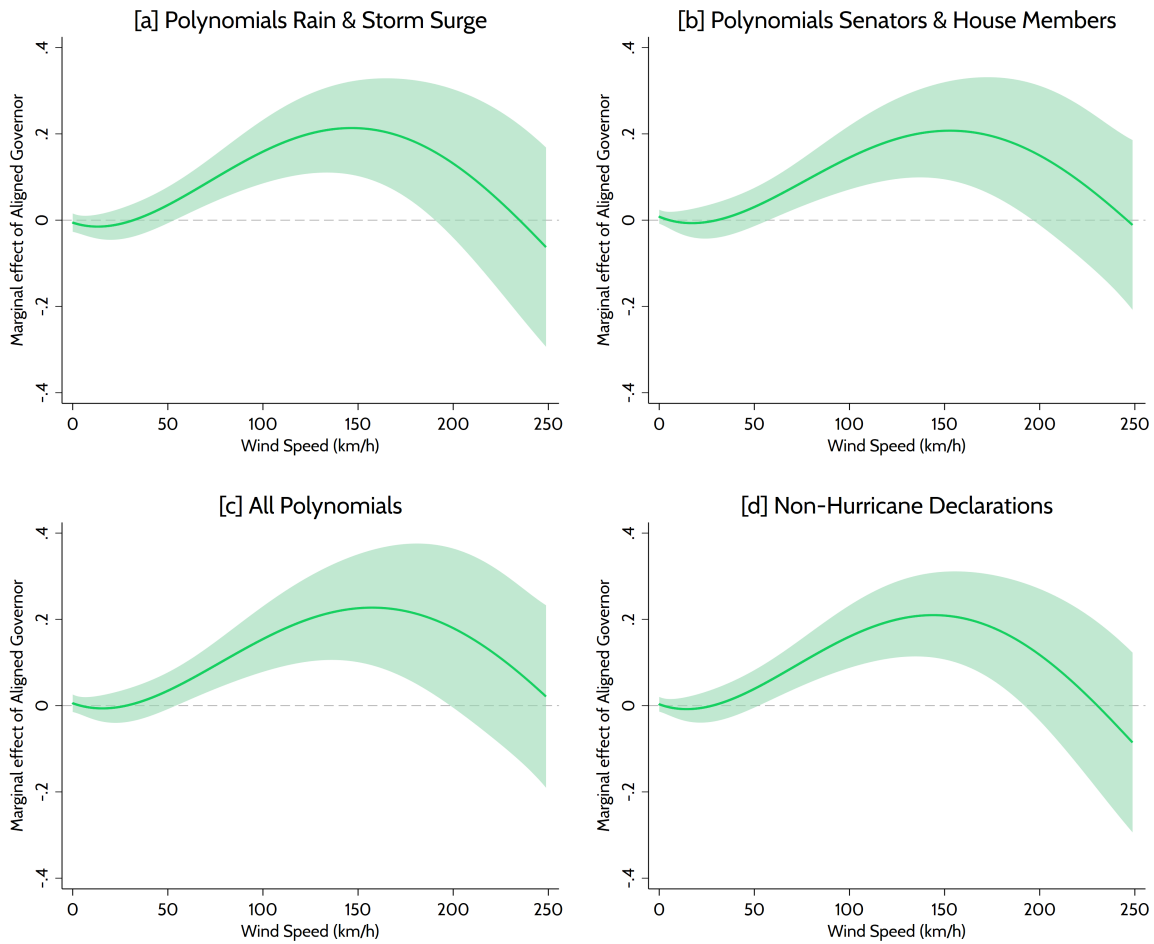


Figure J13: **Robustness: Polynomial Controls and Other Declarations**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state \times year and county level. The sample covers county-year observations from 1965–2018. Panel [a] includes additional polynomial interactions of *Aligned Governor* with *Rainfall* and *Storm Surge* and Panel [b] adds polynomial interactions of *Wind Speed* with *Aligned Representatives* and *Aligned Senators*. Panel [c] allows for all interactions as described in Panels [a] and [b]. In Panel [d], we additionally control for the number of other disaster declarations per county and year.

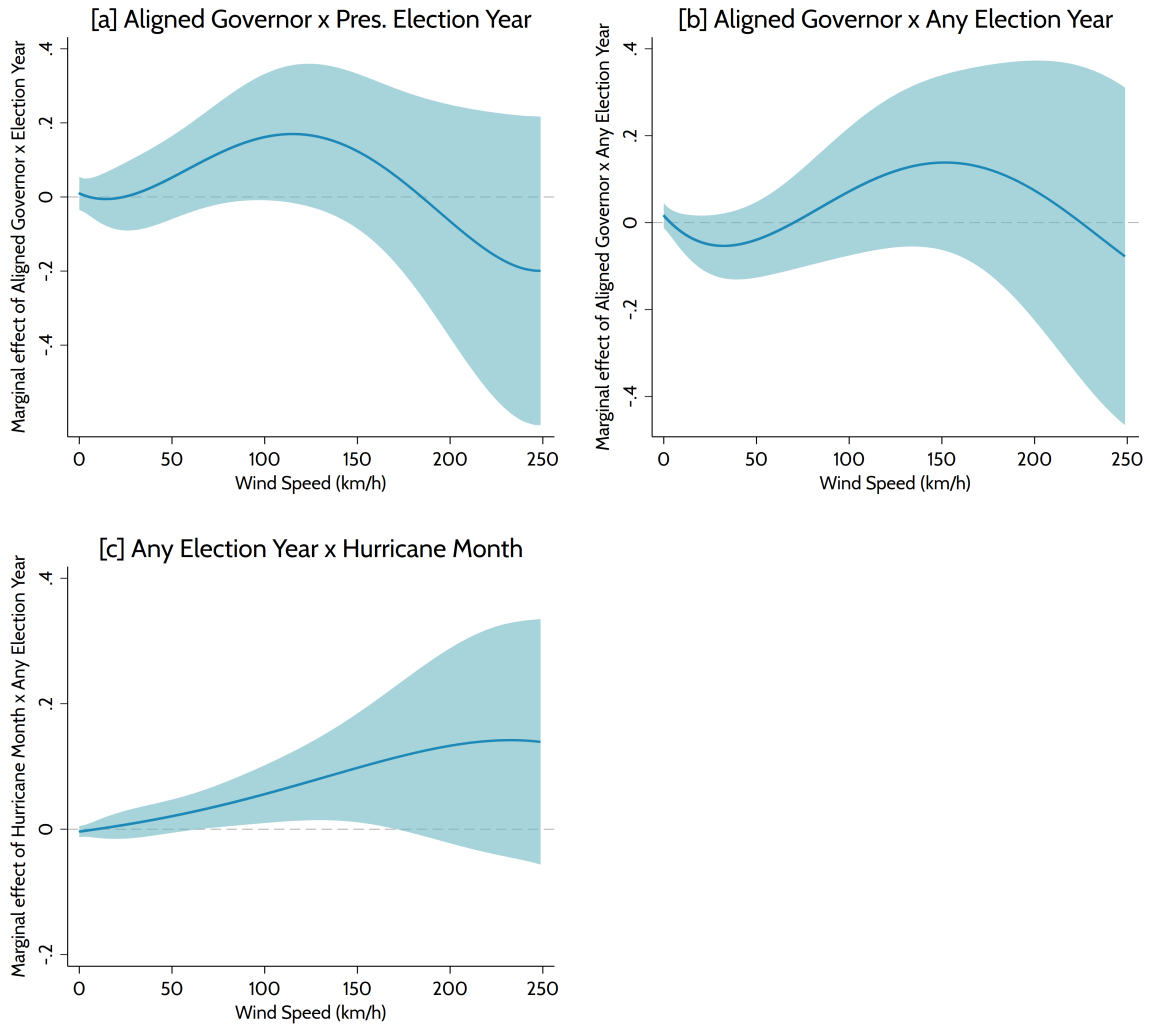


Figure J14: **Political Relief Cycles – Marginal Effects from Triple Interactions**

The figure displays marginal effects for the variable specified on the respective vertical axis from three polynomial estimations including triple interactions. In each specification, we add the depicted variables of interest as well as all possible cross-interactions with the *Wind Speed* polynomial to our baseline for the estimation of heterogeneous effects. Shaded areas represent 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level. In comparison to the triple interaction figure shown in the paper, this figure shows only the marginal effects of the respective triple-interacted coefficients, i.e. displaying the differences in marginal effects between election years and non-election years directly.

K Additional Correlations and Results

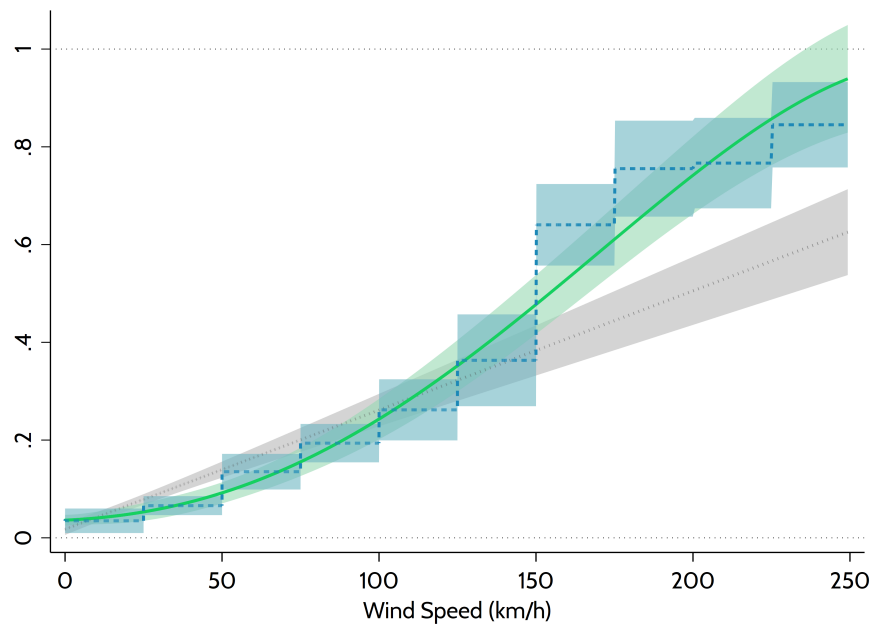


Figure K1: **Relationship of Wind Speeds and Disaster Declarations**

The figure shows the predicted probability for a disaster declaration from three different estimations with *Wind Speed* as the explanatory variable. The specification represented by the black dotted line uses only a linear *Wind Speed* variable, the green solid line applies a quartic *Wind Speed* polynomial, and the blue dashed line applies ten 25 km/h *Wind Speed* bins. All estimations include county- and year fixed effects as well as linear county-specific time trends. The shaded areas show 95% confidence intervals based two-way clustered standard errors on the state \times year and county level.

Table K1: Declaration Turndowns and Relief Amounts

	Declaration	Public Assistance Projects	Total Public Assistance per Capita (log)
	(1)	(2)	(3)
<i>Aligned Governor</i>	-0.003 (0.005) [0.615]	-8.162 (15.953) [0.610]	0.169 (0.206) [0.413]
<i>Aligned Representative</i>	0.001 (0.003) [0.742]	-2.420 (9.615) [0.802]	-0.044 (0.121) [0.717]
<i>Aligned Senators</i>	0.002 (0.005) [0.671]	11.233 (15.914) [0.482]	-0.144 (0.179) [0.421]
Wind Speed Polynomials	X	X	X
Observations	5,459	3,033	3,023

The table displays regression coefficients with two-way clustered standard errors on the state \times year and county level in parentheses. p -values are shown in brackets. All estimations use the linear fixed effects-within estimator and include year fixed effects as well as *Rainfall* and *Storm Surge* controls. ‘Wind Speed Polynomials’ indicates the usage of quartic polynomials. The sample in column 1 includes all county-year observations for which FEMA indicated (via FOIA and openFEMA data) that federal relief has been requested between 1992–2018. In panels 2 and 3 the sample covers all county-year observations for which a federal disaster declaration has been issued and a positive amount of public assistance has been provided (1998–2018).

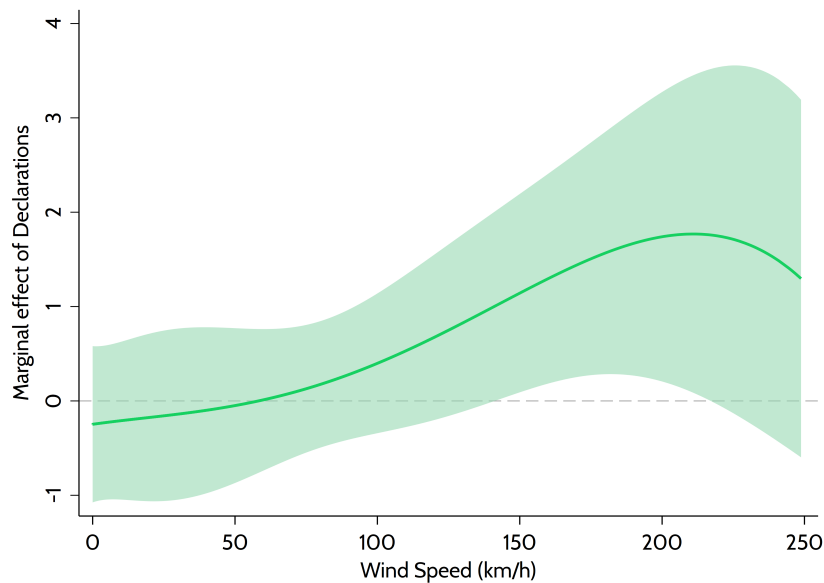


Figure K2: Declarations and Election Outcomes

This figure shows the relationship between issuing a disaster declaration and the change in the incumbent president’s party county-level vote share in the upcoming presidential election, which is the dependent variable in this regression. It displays marginal effects of *Declarations* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying clustered standard errors on the state level. The sample covers county-year observations from 1965–2018.

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