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Disastrous Discretion: Ambiguous Decision Situations Foster Political Favoritism

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Disastrous Discretion: Ambiguous Decision Situations Foster Political Favoritism

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 hurricane strikes from 1965–2018 along with changes in political alignment. We show that decisions are not biased when disasters are unambiguously strong or weak. Only in ambiguous situations, after medium-intensity hurricanes, do areas governed by presidents' co-partisans receive up to twice as many declarations. This political bias explains 10 percent of total relief spending, totaling USD 450 million per year.

JEL-Codes: D720, H300, H840, P160, Q540.

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

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1 Introduction

Favoritism and discrimination pose major societal problems in diverse domains, ranging from individual-level biases to large-scale political favoritism intentionally benefiting entire regions or nations (e.g., Burgess et al., 2015; Chu et al., 2021; Hodler & Raschky, 2014).¹ As the allocation of funds through discretionary mechanisms is a fundamental and unavoidable function of government, it is an important but open question in which situations decisions are susceptible to favoritism and partisan decision-making. Insights from psychology and behavioral economics suggest that biased and discriminatory behavior is most likely when there is ambiguity about the objectively optimal decision.² Ambiguity both leads decision-makers to rely more heavily on prior beliefs, which may be biased, and it creates plausible deniability, reducing the reputational costs of taking partisan decisions.

We show that political decisions exhibit more strategic bias in ambiguous situations. Studying the political reaction to hurricanes, we demonstrate 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. We make use of random spatiotemporal variation in physical hurricane intensities, which cause a wide spectrum of situations of varying severity; ranging from low impact to catastrophic conditions. We quantify the magnitude of the political alignment bias across the full spectrum of hurricane intensities. Our focus is on analyzing when and by how much U.S. presidents favor aligned areas, i.e. those governed by their co-partisans, when allocating federal disaster declarations. To the best of our knowledge, this is the first empirical analysis that reveals how the degree of ambiguity affects the extent of politically biased decision-making in a real-world context.

We provide evidence that strategic politically biased decision-making is less likely when a disaster is either very strong or very weak: the allocation of disaster relief is unambiguously required in the former case and unambiguously superfluous in the latter. In the case of medium-strength disasters, political bias is substantial. In these situations political actors are in a relatively better position to use – or misuse

¹Previous analyses of various political-economic settings provide evidence for different forms of home-region favoritism (e.g., Carozzi & Repetto, 2016; Fisman et al., 2018; Gehring & Schneider, 2018) and increased government spending to politically aligned areas (e.g., Berry et al., 2010; Brollo & Nannicini, 2012; Curto-Grau et al., 2018). In 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, several studies document the existence of political budget cycles and favoritism in the domains of foreign aid, trade, and the Bretton Woods institutions (e.g., Bommer et al., forthcoming; Dreher et al., 2019; 2009; Eichenauer et al., 2020; Faye & Niehaus, 2012; Gassebner & Gnutzmann-Mkrtchyan, 2018; Lang & Presbitero, 2018).

²Experimental and empirical evidence shows that discrimination increases under conditions of ambiguity (Bertrand & Duflo, 2017). For instance, Dovidio & Gaertner (2000) show that recruiters' racial bias in hiring decisions is present when candidate qualifications are ambiguous but not when a candidate is clearly qualified or unqualified. Goncalves & Mello (2021) demonstrate that police officers are less lenient toward speeders from minority groups around a critical threshold in the schedule of penalties. Garicano et al. (2005) present an example for favoritism in individual decision-making under social pressure. They find that soccer referees favor teams playing in front of their home crowd when making decisions about adding more (less) stoppage time when the home team is narrowly trailing (leading). The relationship only exists when the scoreline is close.

– their discretionary power since public opinion on whether it is necessary to provide aid is divided. We show that it is crucial to account for the heterogeneity of biased decision-making because average estimates fall short of capturing the full extent of the alignment bias.

To demonstrate this empirically, we study all hurricane-related federal disaster declarations between 1965–2018. For every hurricane that hit the United States in our 54-year sample period, we apply a physical hurricane intensity model to proxy for the storms’ individual spatial destructiveness. Together with data on partisan alignment, this allows us to estimate the political bias in declaration allocations in response to different disaster intensities. For medium levels of hurricane intensity, the likelihood of a disaster declaration is higher when the president and governor of an affected area are co-partisans. For extremely strong or weak hurricane intensities, in contrast, biased declaration behavior is not prevalent. This nonlinear relationship is not sensitive to functional form assumptions (including state-specific disaster intensity functions and a wide range of high-dimensional polynomial and semi-parametric intensity measures), various subsamples (omitting, for instance, individual decades or states, observations with high leverage and outliers, and focusing on swing states), and permutation-based inference using placebo treatment allocations.

Focusing the analysis on hurricanes has both high socioeconomic relevance and several empirical advantages. First, hurricanes are the most destructive natural disasters in the United States (e.g., [Deryugina, 2017](#); [Deryugina et al., 2018](#); [Hsiang, 2010](#); [Strobl, 2011](#); [2012](#)). Every year within the last decade, hurricanes caused, on average, 536 fatalities and a damage of about USD 60 billion, equivalent to more than 50% of the total annual losses for all major disasters in the U.S.³ Second, given different baseline risks between counties, the timing, location, and severity of hurricane strikes are random and unpredictable (e.g., [Aguado & Burt, 2015](#); [Hsiang, 2010](#); [Strobl, 2011](#)). We make use of the random trajectories and varying physical strengths of hurricanes at different locations and combine new data on all causes of hurricane damage (wind speed, rainfall, and storm surge) with variation in political alignment. This allows us to evaluate the extent of political bias in presidential disaster declarations with respect to disaster intensity.

To isolate the political effect, we focus on the president’s binary choice to declare an event a disaster or not. A federal disaster declaration is the requirement for relief provision by the Federal Emergency Management Agency (FEMA). Relief payments from FEMA are important in magnitude, averaging about USD 8 billion per year between 2009 and 2018.⁴ Disaster declaration decisions are a unilateral

³See <https://www.ncdc.noaa.gov/billions/>, last accessed January 11, 2021. For general socioeconomic effects of hurricanes cf., for instance, [Barrage & Bakkensen \(2021\)](#), [Elliott et al. \(2015\)](#), [Fried \(forthcoming\)](#), and [Kunze \(2021\)](#); for extreme climate and weather events in general see, e.g., [Auffhammer \(2018\)](#), [Dell et al. \(2012\)](#), [Felbermayr & Gröschl \(2014\)](#), [Hsiang et al. \(2017\)](#), [Kalkuhl & Wenz \(2020\)](#), [Klomp \(2016\)](#), [Kotz et al. \(2022\)](#), and [Noy \(2009\)](#).

⁴See <https://www.washingtonpost.com/us-policy/2019/04/22/taxpayer-spending-us-disaster-fund-explodes-amid-climate-change-population-trends/>, last accessed September 3, 2021. Data on the actual relief amounts paid out by FEMA for hurricane disasters to individual counties are only available for a limited period starting in 1998.

power of the U.S. president (Gasper & Reeves, 2011). While governors can request federal declarations from the president, they naturally decide whether to send a request in anticipation of how the president will respond.⁵ The president does not decide actual relief amounts – which are determined by FEMA bureaucrats during the recovery phase in the years to follow – but decides which counties a declaration covers. Our main analysis hence focuses on disaster declarations as the outcome of the political process. Consequently, we observe a quasi-experiment in which presidents must respond to a wide variety of random shocks whose location, timing, and magnitude are determined by a stochastic meteorological process. Hurricanes thereby trigger the political decision-making process. Based on the observed disaster intensity, the president has to make a decision as to whether a federal disaster declaration is necessary. Since the hurricane season usually ends before major elections take place in November, political factors are predetermined when the disaster strikes; in particular, the governor of an affected state, who requests federal relief from the president, is either politically aligned or unaligned with the president. To capture the causal political alignment effect for different storm intensities, we employ within-county estimations that compare the same county with itself over time in periods of alignment and unalignment, controlling for year, county-by-decade fixed effects, and random hurricane intensity. That is, we exploit the fact that counties are hit by hurricanes in different years to estimate whether the same county is more likely to receive a disaster declaration if a hurricane of a certain strength happens to strike during a period in which the governor is a co-partisan of the president.⁶ 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 for a given storm intensity.

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 four-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 more than four times more important for medium-strength disasters. The probability of observing a disaster declaration in an area with medium damage increases by up to 18 percentage points, almost doubling the declaration likelihood, 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. Additionally, we show evidence suggesting that the primary mechanism operates at the intensive margin: “aligned” declarations include on average more counties with relatively

⁵Data on governors’ declaration requests are not publicly available. The data that we received via a Freedom of Information Act inquiry from FEMA has stark temporal limitations and suffers from anticipatory obedience. Analyses with these data yield insignificant results, which we report in the appendix for completeness. For further details about the relief system, see Section 2.1 and Appendix A.

⁶In our 54 years-spanning panel, we observe ample variation for all relevant variables to apply FE-within estimations. 48,781 observations from 1,136 counties in our main sample were both affected by hurricanes (wind, precipitation, or storm surge) in multiple years and exhibit a different alignment status in at least one treatment year. On average, 124 counties per year receive a declaration in our data.

weaker wind intensities. Considering the heterogeneity of the political bias, the hurricane-intensity and population distributions, as well as average declaration probabilities and payments for different wind intensities, we calculate that the political alignment bias for hurricane-related disasters amounts to approximately USD 450 million on average per year. This corresponds to approximately 10% of total annual hurricane relief payments. We demonstrate that it is important to account for the bias heterogeneity. The assumption of average effects would underestimate the total magnitude of biased allocations because most relief is issued for moderate disasters – where the bias is strongest – as compared to rare extreme events (cf. Appendix I).

We show that politicization in the disaster declaration process emerges in the post-1988 period. The emergence of politicization coincides with the passage of the Stafford Act in 1988, which augmented the position of the president to make discretionary – and potentially politically biased – decisions about what qualifies for disaster declarations (Lindsay & McCarthy, 2015; Reeves, 2011; Sylves, 2008). We also document the declaration bias at intermediate storm intensities for presidential alignment with other politicians and in subsamples of close election outcomes, where it is essentially random whether the incumbent governor and president happen to be aligned. We do not find significant differences in declaration behavior between Democrats and Republicans. Several results are consistent with a strategic electorally-motivated explanation of our findings: areas with low electoral support for the president's party receive fewer declarations, the alignment bias is more pronounced for governors who have been elected with smaller margins, and *ceteris paribus*, disaster declarations for storms occurring closer before elections are more likely.

Our findings add to several strands of the literature. First, our contribution extends the literature on the alignment bias in intergovernmental transfers. Various studies document an alignment bias for different countries (e.g., Brollo & Nannicini, 2012, for Brazil; 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 relationships in the literature are conclusive. Our analysis shows that politicians' strategic behavior yields a nonlinear political bias, which implies a grave underestimation of biased decision-making in ambiguous situations as well as the total misallocation of disaster relief funds. In general, our results yield an important insight into the partisan behavior of executive politicians as they extend our understanding of when political actors make efficient decisions and in which situations decision-making processes require modification or enhanced monitoring.

Second, we show that ambiguity plays an important role not only in experimental settings but also in a real-world environment. This finding connects evidence from behavioral economics and psychology – showing that ambiguous situations foster racism and biased decision behavior (Bertrand & Duflo, 2017; Dovidio & Gaertner, 2000; Gaertner et al., 2008) – to political decision-making. While the discriminatory biases that the existing literature documents are often unintentional and not necessarily beneficial for the individuals exercising them, political allocation decisions are, on the contrary, both executed deliberately and electorally beneficial (e.g., Cole et al., 2012; Levitt & Snyder, 1997; Manacorda et al., 2011). We provide the first empirical analysis showing that for discretionary political decisions, a similar logic applies regarding the degree of ambiguity involved.

Third, our results relate to the literature showing that political bias increases when the electorate does not clearly expect a particular action. Focusing on the importance of media attention, Durante & Zhuravskaya (2018) and Djourelouva & Durante (2022) 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 insight from our analysis is that politicians do not necessarily require 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.

Fourth, in studying executive decision-making in the United States, we add to the literature on U.S. distributive politics documenting politically biased fund allocations.⁷ 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 (Garrett & Sobel, 2003; Gasper, 2015; Reeves, 2011). Our new fine-grid physical data allow us to provide a more precise analysis and to double the studied time horizon. We demonstrate the heterogeneous pattern of the political alignment bias, which would otherwise be covered in average effects. This refinement is crucial for all decisions where the outcomes of the allocation decisions are heterogeneous. That is, average effects are misleading when the expected political and economic gains of a decision are not homogeneously distributed. This is the case, for instance, for relief spending, where the relatively high number of moderate events corresponds to a large share of fund allocations.

The paper is structured as follows: we first introduce the institutional background and discuss the role of ambiguity for the analysis of politically-biased decision making. 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 presents the results from the empirical estimations and provides various sensitivity tests. The paper concludes with a discussion of the implications of our

⁷Existing studies find evidence for biased spending favoring areas with higher electoral support (Dynes & Huber, 2015; Larcinese et al., 2006), presidents' co-partisan House members (Berry et al., 2010; Kriner & Reeves, 2015), members of the Congress majority party (Albouy, 2013), and for political budget cycles (Bostashvili & Ujhelyi, 2019; Enikolopov, 2014).

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 first provide a brief explanation of the disaster declaration system that we study in our empirical analysis. We then explain results from the literature on political allocation decisions. Putting an emphasis on the alignment bias and its theoretical background, we discuss how the degree of situational ambiguity affects politicians' decision behavior.⁸ We argue why it is crucial to consider the implied bias heterogeneity to capture the true pattern and magnitude of the political bias.

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.⁹ 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.

The passage of the Robert T. Stafford Disaster Relief and Emergency Assistance Act (Stafford Act) in 1988, which represents the current legal basis for federal disaster declarations, was the most significant amendment of disaster relief legislature. It augmented the discretionary power of the president to decide which events qualify for a declaration (Reeves, 2011; Sylves, 2008).¹⁰ The president issues a

⁸In Appendix B, we formalize the role of ambiguity in a theoretical model and derive the alignment bias. This model is based on previous work by Arulampalam et al. (2009) and Solé-Ollé & Sorribas-Navarro (2008) on the political economy of fiscal federalism and central government grant allocations with different levels of government (cf. also Bracco et al., 2015; Curto-Grau et al., 2018; Dixit & Londregan, 1998; Geys & Vermeir, 2014). While we apply the model to the case of natural disasters, the framework would in principle be generalizable to other types of discretionary allocation decisions that concentrate benefits in certain regions while being financed through general taxes and where decisions about eligibility in ambiguous cases have to be made. This applies, for instance, to international development aid, redistribution schemes intended to support economically weaker regions, or funds allocated according to eligibility criteria (see, e.g., Asatryan & Havlik, 2020; Budjan & Fuchs, 2021; Gehring & Schneider, 2018; 2020; Michaelowa et al., 2018).

⁹To 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.

¹⁰With the objective of not categorically precluding any geographic area or event from federal relief (for example, by rigidly applying some formula or sliding scale) and to ensure that action for relief could be taken quickly, the language in the

declaration to a specific state and explicitly lists the counties eligible for federal help.¹¹ Only contingent upon a presidential disaster declaration can FEMA then initiate its work on site. Crucially, FEMA determines the amount of financial assistance needed and decides which individuals or public entities in the declared area are eligible for relief.

While “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” (ibid., p. 94). Due to this “unilateral authority” (Gasper & Reeves, 2011), the behavior of the president eventually determines whether the allocation of declarations is politically biased. In the following, we discuss in which situations politically biased decisions are most likely.

2.2 Politically Biased Decision-Making and the Role of Ambiguity

The allocation of disaster relief is not only economically but also politically meaningful. For instance, 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.¹²

Since relief allocation can affect future electoral success, electorally-motivated politicians might consider strategic interests when making their decisions about disaster relief allocation and there is empirical evidence for such biased behavior. For example, Gasper (2015), Garrett & Sobel (2003), and Reeves (2011) show evidence for political bias on average towards electorally competitive and strategically important states as well as co-partisans. Politically biased government spending is an issue that is not exclusive to disaster relief. Results by Berry et al. (2010), Dynes & Huber (2015), and Larcinese et al. (2006) show, for instance, that districts and states that are governed by co-partisans of the U.S. president receive more federal outlays.

An important factor in government allocation decisions is the alignment of key political actors at different levels of government; i.e., in case of U.S. disaster declarations whether the relief-requesting governors and the president, who decides which counties receive a declaration, are co-partisans. In-

Stafford Act is very vague and leaves the president with full discretion when to issue a declaration (Gasper, 2015; Lindsay & McCarthy, 2015; Reeves, 2011; Sylves, 2008). The Stafford Act emphasizes that the president can issue a declaration for any “natural catastrophe (including any hurricane, tornado, storm, [...]), or, regardless of cause, any fire, flood, or explosion in any part of the United States, which in the determination of the president causes damage of sufficient severity and magnitude” (Stafford Act, 1988). Furthermore, the Stafford Act increased the potential resources available under a declaration by introducing, e.g., the hazard mitigation program (cf. Sylves, 2008). See Appendix A.2 and A.3 for details about the different types of disaster declarations and spending programs.

¹¹While 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” (ibid., p. 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).

¹²See also the evidence presented by Bechtel & Hainmueller (2011) for Germany, Cole et al. (2012) for India, Lazarev et al. (2014) for Russia, and Healy & Malhotra (2009) for the United States. Note that a recent reanalysis of Gasper & Reeves (2011) by Gallagher (2021) finds no evidence for attentive behavior of the electorate.

centives to favor aligned politicians are manifold as presidents 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., 2022; Zudenkova, 2011). In the aligned case, a party can exclusively take credit for a declaration and receive the electoral reward (cf. Arulampalam et al., 2009; Geys & Vermeir, 2014; Solé-Ollé & Sorribas-Navarro, 2008). Empirical evidence from multiple countries shows the existence of alignment biases in intergovernmental transfers (e.g., Bracco et al., 2015; Curto-Grau et al., 2018; Fiva & Halse, 2016; Quinckhardt, 2019).

We argue that previous studies do not capture the full magnitude of politically biased decision-making. As we demonstrate, the alignment bias in allocation decisions is a more grave issue when we drop the assumption of a homogeneous bias. The effect heterogeneity emerges because political actors face a variety of decision situations, which we can characterize as more or less ambiguous in terms of the most appropriate decision. Our argument is based on the fact that electorally-motivated politicians are confronted with *de facto* constraints in their ability to act opportunistic (cf. Ansolabehere & Rogowski, 2020; Christenson & Kriner, 2019). The political drawbacks of acting against the prevalent public opinion increase as there is more consensus.

When it comes to natural disasters and political decisions about disaster relief, the public forms an opinion about whether it is appropriate to provide relief to a specific place based on the observed disaster strength.¹³ For extreme disaster intensities, there is a public consensus that a disaster declaration is necessary. For weak disaster intensities, a large majority in the public will not find it appropriate to allocate public money (Bechtel & Mannino, 2020). In both cases, vote-maximizing politicians anticipate the potential electoral backlash that a declaration decision in opposition of public expectation could entail. No matter what the political constellation or incentives may be, the politician will likely issue a declaration in the first case but not the latter.

However, there are more ambiguous decision situations. For medium-intense disasters, it is less clear whether relief is required. In this case, political incentives can be the factor to tip the scales. We would expect any systematic political bias to be most pronounced here. For instance, presidents may choose to

¹³Disasters and decisions about relief are usually accompanied by substantive media coverage and public attention. The media plays an important role as an intermediary in disaster assistance by communicating information to the electorate. Eisessee & 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) and Snyder & Strömberg (2010) find that federal spending in the U.S. is higher in areas with better radio reception and press coverage of politicians, respectively. 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 theoretical model in Appendix B to capture the consequences of different levels of national public attention.

include a moderately-affected county in a disaster declaration if the requesting governor is politically aligned but not if the same area was politically unaligned.

This suggests that decisions in some situations are susceptible to a strong political bias while others are not. The actual magnitude of political bias would be disguised in moderate or insignificant findings when averaging over all decision situations. With our detailed hurricane intensity data (see Section 3), we can test the exact pattern and strength of the alignment bias. We also examine further factors like election years, the degree of electoral competitiveness, regional concentration of loyal supporters, etc. that could amplify this effect (cf. [Gasper, 2015](#)).¹⁴ Making use of the continuous and exogenous treatment, which covers the full range of storm intensity from very light to catastrophic – and the implied degree of ambiguity – we can overcome underestimating the political bias in critical allocation decisions.

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.¹⁵ 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, 2021](#); [Strobl, 2011](#)). To account for all possible sources of hurricane damage, we additionally use new rainfall and coastal flooding data. However, as rainfall is highly localized and storm surge occurs only in coastal counties, we utilize wind intensity as our primary damage proxy while always controlling for the other two factors.

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

¹⁴Most related evidence on political budget cycles exists for developing countries and young democracies ([Aidt et al., 2019](#); [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. [Hessami \(2018\)](#) documents electoral cycles in grant allocations for elected but not for appointed German mayors, and [Bjørnskov & Voigt \(2020\)](#) show cycles in state of emergency declarations after terrorist attacks.

¹⁵See Appendix D for details about hurricane genesis and impacts.

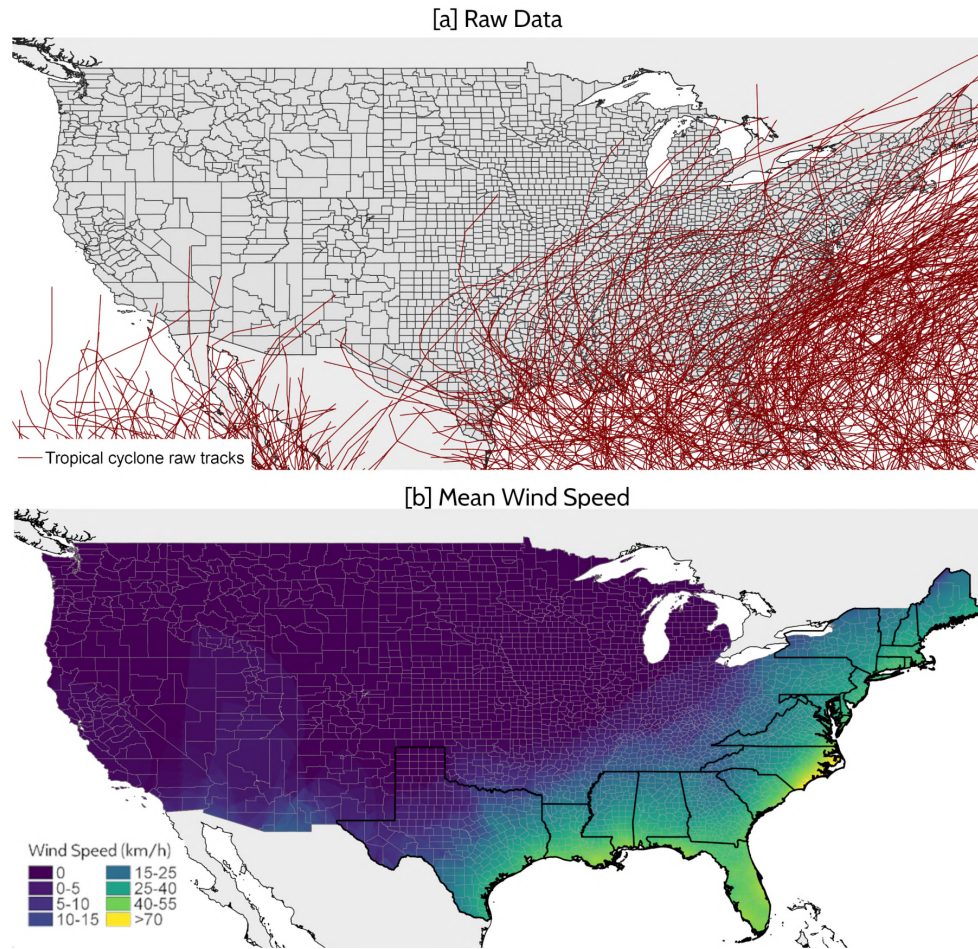


Figure 1: **Hurricane Raw Tracks and Modeled *Wind Speed* Average, 1965–2018**

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 thick black edging encircles the states covered in our baseline sample. This sample contains all counties in states with an Atlantic or Gulf of Mexico coast line. Appendix Figure H1 displays how often individual counties have been affected by tropical cyclone-related *Wind Speed*, *Rainfall* or *Storm Surge*.

of hurricanes. To calculate spatial destructiveness, we apply the implementation of the meteorological CLIMADA model (Aznar-Siguan & Bresch, 2019) by Kunze (2021), 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, our data contains information on 325 tropical cyclones. Panel [b] of Figure 1 displays the average wind speed exposure over the 1965–2018 period, as derived from our wind field model. Our baseline sample focuses on coastal states (Atlantic and Gulf of Mexico coastline) as they experience the predominant share of hurricane-related damage.

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; Strobl, 2011). Appendix Figure H2 shows the strong relationship between *Wind Speed* and the likelihood of observing a disaster declaration.¹⁶

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.

In comparison to other political-economic studies, the usage of the physical intensity data is an advancement. Previous 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, truncation, missing data, and endogeneity (see Appendix C; Felbermayr & Gröschl, 2014; Gallagher, 2021; Kousky, 2014). We circumvent these problems by applying objective and exogenous physical intensity measures to proxy for damage from hurricanes.¹⁷

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

¹⁶For wind intensities above 200 km/h, the probability to observe a disaster declaration in a county is around 80% or higher, while declaration probabilities for wind speeds below 90 km/h are less than 20%. The exposure to hurricanes varies significantly over time and space. Appendix Figure E3 displays the annual variation of the *Wind Speed* variable at the county level. 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. The majority of the affected counties (67%) 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.

¹⁷Furthermore, compared to previous studies on U.S. disaster relief allocation, which cover 8 to 25 years (Garrett & Sobel, 2003; Gasper, 2015; Reeves, 2011), we double the time horizon of the analysis with our 54 years-spanning county panel.

our indicator.¹⁸ We also present results with a separate indicator for emergency and major disaster declarations. In our data, 6,553 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 G8).

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. On average, the *Aligned Governor* status changed 10.8 times for an individual county during the 54 years of our sample. Analogously, we construct binary variables for congressional politicians' party affiliations (*Aligned Representative*) and for the two incumbent senators (*Aligned Senators*) being co-partisans of the president.²⁰

Additionally, we exploit data on past election outcomes to test further political channels. For instance, we use different variables measuring electoral support and competitiveness of the incumbent president in states and counties. 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.

Our baseline sample covers all county-year observations with positive *Wind Speed*, *Rainfall*, or *Storm Surge* observations from the states bordering the Atlantic or Gulf of Mexico (see Figure 1). The final

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. Using the number of declarations as a dependent variable might cause problems due to double declarations (emergency and major disaster declarations) for the same disaster (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 alignment indicators capture politicians' party affiliations at the beginning of November (i.e., at the point of a potential presidential election). In case of independents, we code them as 0. We 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.

panel data set consists of 49,092 county-year observations over the 1965–2018 period. As robustness tests, we also show results for a panel of all affected counties from the contiguous United States and a fully balanced panel including observations not affected by a hurricane in a specific year, which inflates the data set with zeros (see Appendix Figure H3). 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>	49,092	0.11	0.31	0.00	1.00
<i>Emergency Declaration</i>	49,092	0.05	0.22	0.00	1.00
<i>Major Declaration</i>	49,092	0.09	0.29	0.00	1.00
<i>Declarations</i>	49,092	0.15	0.50	0.00	5.00
<i>Aligned Governor</i>	49,092	0.44	0.50	0.00	1.00
<i>Aligned Representative</i>	49,092	0.46	0.50	0.00	1.00
<i>Aligned Senators</i>	49,092	0.30	0.46	0.00	1.00
<i>Alignment Count</i>	49,092	1.89	1.28	0.00	4.00
<i>Wind Speed</i>	49,092	34.55	41.77	0.00	352.71
<i>Rainfall</i>	49,092	69.46	78.48	0.00	1,538.73
<i>Storm Surge</i>	49,092	0.07	0.35	0.00	6.01
<i>Hurricane Month</i>	48,808	8.26	1.39	5.00	11.00

See Appendix Table F1 for the full summary statistics.

4 Empirical Strategy

We analyze 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. Our setting allows us to identify systematic political biases in the outcome of the declaration process, in which the president makes the final decision.

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, engagements in different forms of log-rolling, or ideological alignment of incumbents and their electoral base regarding distributive policies. Usually, executive politicians can also control the timing of their decisions to a certain extent as part of an endogenous process.

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, 2021; 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 exogenously trigger the political decision-making process (i.e., politicians cannot opt-out or postpone their decision). At the point in time when politicians are prompted to make a declaration decision, 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. That implies decision situations involving different levels of ambiguity as to whether a declaration is necessary. As explained in the previous section, we rely on the assumption that stronger hurricanes, *ceteris paribus*, cause more damage.²¹

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 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 and mitigation efforts, county infrastructure, or the vulnerability of the population may have changed over time. To account for such potentially nonlinear trends in unobserved factors in a flexible way, our baseline estimation includes county \times decade fixed effects. Accordingly, the following least-squares estimation equation represents the starting point for our analysis:

$$Declaration_{i,t} = \alpha + \beta Aligned\ Governor_{s,t} + \gamma Wind\ Speed_{i,t} + \mathbf{X}'_{i,t} \mu + \tau_t + \sigma_i \times \zeta_t + \varepsilon_{i,s,t} \quad (1)$$

²¹The main estimation approach assumes that a certain level of wind speed corresponds to equal need for a disaster declaration at each location. To 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. Appendix Figure H4 demonstrates that our results do not depend on the assumption of a nationwide uniform resilience level.

where *Declaration* is the binary indicator for disaster declarations received by county i in year t .²² 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 year fixed effects (τ_t) and county \times decade fixed effects ($\sigma_i \times \zeta_t$); $\varepsilon_{i,t}$ 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 G2 and Figure H5 that our results do not change significantly when we add a vector of lagged socioeconomic control variables including county-level income, population, and race.²³

Equation (1) takes a strict linear approach in modeling storm damage and the average political influence over all storm intensities. By abandoning it, 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. Most importantly, 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

$$\begin{aligned} \text{Declaration}_{i,t} = & \alpha + \beta \text{Aligned Governor}_{s,t} + \sum_{b=1}^4 \gamma_b \text{Wind Speed}_{i,t}^b \\ & + \sum_{b=1}^4 (\delta_b \text{Wind Speed}_{i,t}^b \times \text{Aligned Governor}_{s,t}) + \mathbf{X}'_{i,t} \mu + \tau_t + \sigma_i \times \zeta_t + \varepsilon_{i,s,t}. \end{aligned} \quad (2)$$

We aim for a parsimonious baseline model so as to not inflate the regression unnecessarily with additional parameters, which allows us to analyze smaller subsamples or to add further interactions. Based on a

²²We estimate least-squares FE-within regressions using the `reghdfe` command (written by Correia, 2017) in Stata. For robustness, Appendix Table G1 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. Figure H4 demonstrates robustness to applying county-specific linear time trends and within-decade county-specific linear time trends as an alternative to county \times decade fixed effects.

²³Our main results are also robust when we flexibly control for these covariates by interacting them with our *Wind Speed* variables (Appendix Figure H5, Panel [b]). In Appendix Figure H7, we show that there exists no systematic relationship regressing these pre-hurricane socioeconomic variables on our main variables of interest, conditional on the same set of controls and fixed effects. To further alleviate concerns about the correlation of alignment with observable characteristics, we show that weighted specifications applying entropy balancing, which ensures a sample balanced on these pre-treatment characteristics regarding one dimension of our treatment, do not yield different results (Appendix Figure H6).

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 Figure H8).²⁴

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 declaration and we can estimate a separate marginal effect of the interacted political factor for every wind intensity interval.²⁵

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 incumbents win the election by a very close margin, it is quasi-random whether a state is politically aligned or unaligned with the president because the alignment status changes discontinuously at the 50% threshold (see, e.g., Brollo & Nannicini, 2012; Eggers et al., 2015; Pettersson-Lidbom, 2008).

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 account for both the correlation of our complex $\text{WindSpeed}_{i,t}^b \times \text{AlignedGovernor}_{s,t}$ treatment within state-years, due to the statewide unity of the alignment status per hurricane season, and the potential correlation of county outcomes over time, we cluster standard errors at the state \times year and county level

²⁴To 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 G3 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 that the political influence is nonlinear.

²⁵The *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.

as our baseline (cf. Kousky et al., 2018). Appendix Table G4 and Figure H9 show that our results are robust to all possible conventional choices of clustering the standard errors, which include clustering at the county, county & year, state, year, state & year, and hurricane level. Additionally, the results are also robust to applying spatial HAC-errors (Colella et al., 2019), which allow standard errors to be correlated within different radii (500, 750, 1000 km) 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 49,092 county-year observations affected by a hurricane in coastal states from 1965–2018. Our estimations control for storm intensity directly. In all regressions, coefficients of *Wind Speed* and *Rainfall* are highly significant, explaining a large share of the overall variation in disaster declarations.²⁶ 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 in *Wind Speed* (approx. 40 km/h) raises the probability of a disaster declaration by about 8.6 percentage points.

The second column adds our main variable of interest, *Aligned Governor*. The estimated coefficient of 0.048 is highly significant with a p -value of 0.008. It signifies that, *ceteris paribus*, counties have, on average, a 4.8 percentage point higher chance of receiving a disaster declaration if the president and the governor are aligned. The coefficient of *Aligned Governor* only diminishes slightly when including other political variables of interest. *Aligned Representatives* and *Aligned Senators* are also related to a higher

²⁶*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.

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

Dep. var.: <i>Declaration</i>	(1)	(2)	(3)	(4)	(5)	(6)
<i>Aligned Governor</i>		0.048 (0.018)	0.044 (0.018)	0.044 (0.019)	0.043 (0.019)	0.042 (0.019)
<i>Aligned Representative</i>			0.018 (0.007)	0.021 (0.008)	0.021 (0.008)	0.021 (0.008)
<i>Aligned Senators</i>			0.019 (0.021)	0.018 (0.031)	0.021 (0.031)	0.021 (0.031)
<i>Wind Speed (St. Dev.)</i>	0.086 (0.008)	0.086 (0.008)	0.087 (0.008)	0.084 (0.009)		
<i>Rainfall (St. Dev.)</i>	0.076 (0.006)	0.076 (0.006)	0.076 (0.006)	0.081 (0.006)	0.081 (0.006)	0.082 (0.006)
<i>Storm Surge (St. Dev.)</i>	0.024 (0.009)	0.023 (0.009)	0.023 (0.009)	0.024 (0.010)	0.000 (0.010)	0.000 (0.009)
County × decade FE				X	X	X
<i>Wind Speed</i> polynomial					X	
<i>Wind Speed</i> bins						X
Alternative SE: <i>Aligned Gov.</i>						
State & year cluster		0.023	0.020	0.024	0.024	0.023
Spatial cluster		0.023	0.021	0.022	0.022	0.021
Dep. var. mean	0.107	0.107	0.107	0.107	0.107	0.107
Observations	49,092	49,092	49,092	49,092	49,092	49,092

The table displays regression coefficients with two-way clustered standard errors on the state × year and county level in parentheses. The number of clusters is 927 in the state-year dimension and 1,136 in the county dimension. All estimations use the linear fixed effect-within estimator and include county and year fixed effects (Appendix Table G1 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 are 40.59 km/h for *Wind Speed*, 79.04 mm for *Rainfall*, and 0.81 m for *Storm Surge*. Models 4–6 replace county fixed effects with county × decade fixed effects. “*Wind Speed* bins” signifies the usage of the semi-parametric approach to model wind speed, and “*Wind Speed* polynomial” indicates the usage of quartic polynomials. For the main variable of interest *Aligned Governor*, we show standard errors based on two alternative clustering adjustments below the regression results: two-way clustering on the state & year level and a spatiotemporal HAC-robust clustering with 1000 km and a 10 year cutoff. Appendix Table G4 documents robustness toward alternative clustering choices for all explanatory variables. “Dep. var. mean” denotes the mean of the dependent variable. The sample runs from 1965–2018 in all regressions.

probability of receiving a disaster declaration (column 3). The coefficient for senators is insignificant, however. Unlike governors, representatives and senators are not directly involved in the process of requesting declarations but they can lobby the president, for example, by writing supporting letters for governors’ requests.²⁷ The coefficients of interest barely change when we allow for the existence of county-by-decade fixed effects, which account for structural changes affecting the baseline probability of a county receiving federal disaster relief in a flexible way, in column 4.

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 bias. The previous approach treats all situations as equal in terms of potential exertion of political influence. However, as Section 2.2 and Appendix B outline, we hypothesize that the strength of political effects is very heterogeneous and dependent on the situation politicians are faced with. Attempts to capture the alignment effect with a single parameter thus involve stark assumptions and simplifications.

²⁷As 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.”

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 ten 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.²⁸

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 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 2 shows marginal effects of *Aligned Governor* for observing a disaster declaration at different levels of *Wind Speed*. 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, but the estimates are quantitatively similar. While point estimates are close to zero and insignificant for weak wind speeds, the marginal effect of alignment increases with storm intensity, becoming significant at the 95% confidence level at around 50 km/h (31 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 135 km/h (84 mph) in the polynomial and the 125 km/h (78 mph) to 150 km/h (93 mph) interval in the semi-parametric approach. At its maximum, the estimated marginal effect is 0.18 in the polynomial estimation. This is about four times higher than the average relationship from Table 2 and corresponds to almost doubling the likelihood of a declaration for medium hurricane intensities (cf. Appendix Figure H10), which underlines the scope of heterogeneity present in political effects. Marginal effects decrease again for stronger wind speeds, turning insignificant for observations higher than 178 km/h (110 mph).

The importance of accounting for the distinct heterogeneity of the relationship also becomes evident when making a calculation of the associated political share of relief payments. The political bias is most

²⁸To show the robustness of the average effects, we run several specifications. Appendix Table G1 demonstrates that our results are robust to different regression model choices (logit, probit, Poisson, Poisson pseudo-maximum likelihood). Finally, our findings also 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 G2). Appendix Table G5 includes variables for past *Declaration* and past *Wind Speed*.

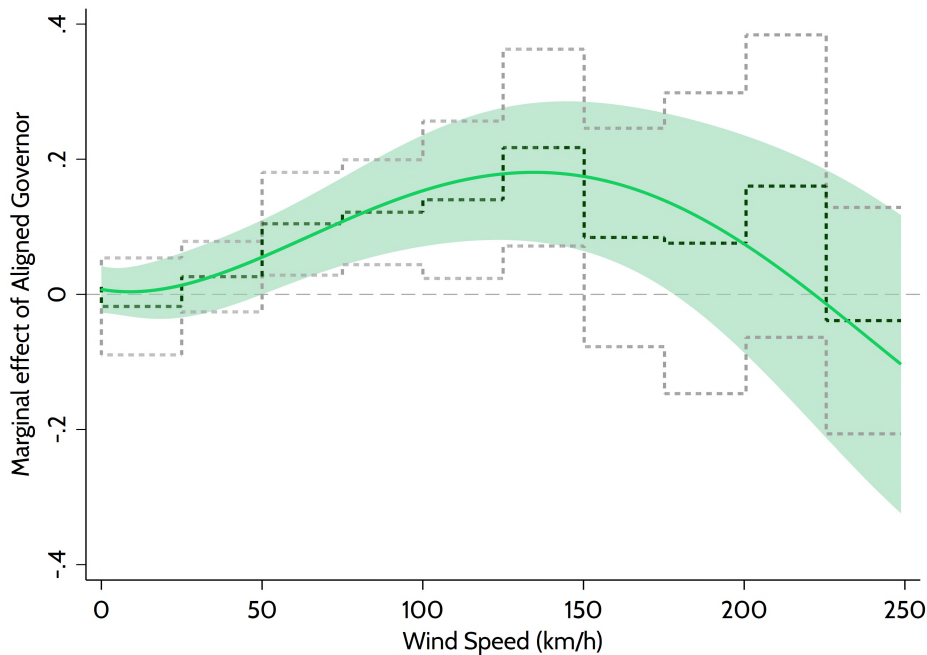


Figure 2: **Alignment Bias for Different Levels of *Wind Speed***

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. Marginal effects for *Aligned Governor* are derived from the main effect and its interaction coefficients with the *Wind Speed* polynomial (i.e., $\beta + \delta_1 \text{Wind Speed} + \delta_2 \text{Wind Speed}^2 + \delta_3 \text{Wind Speed}^3 + \delta_4 \text{Wind Speed}^4$) or the ten *Wind Speed* bins, respectively. 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 number of clusters is 927 in the state-year dimension and 1,136 in the county dimension. The sample covers 49,092 county-year observations from 1965–2018.

pronounced for intermediate wind speeds but the largest payments are related to extreme events, which occur less frequently. To provide a credible estimate of the political share of disaster relief, we consider the following factors: per capita payments associated with a certain storm intensity, the probability that a storm event of a specific intensity entails a declaration, the average population affected by a certain wind intensity, the annual distribution of storm strengths, and the pattern of the nonlinear political bias. Appendix I explains the steps we perform for our estimations in detail. We calculate that the political component of hurricane relief amounts to roughly USD 450 million per year. This corresponds to about 10% of the estimated total annual hurricane relief (FEMA, 2019b).²⁹

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),

²⁹Note that this figure only contains FEMA's public assistance and individual assistance but no other spending categories such as, for example, hazard mitigation. 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).

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 that political discretion yields a bias in disaster declaration outcomes when the degree of ambiguity for declaration need is high. 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.

There are two possible explanations of the relatively big magnitude of our coefficient: the effect could be operating at an extensive or intensive margin. An effect at the extensive margin would mean that, being faced with same medium-strength storm event, the president would be more likely to grant a declaration in an aligned state, i.e., the actual probability of observing any declaration for a sub-group of affected counties in that state-year is higher. If the effect operates at the intensive margin, presidents would include more marginal counties into declarations that are allocated to aligned states, *ceteris paribus*. As the attention of the media and the public rather focuses on the most strongly affected areas, this seems a more likely explanation for the strong effect we find.

To further analyze our effect in that regard, we aggregate our data at the state level and reduce the full sample to all state-year observations for which we observe a declaration. If the intensive margin channel applies, the marginal county included in a declaration should feature a lower storm intensity, on average, in aligned compared to unaligned situations. Table 3 displays three regressions to test whether this applies. We regress the *Lowest Wind Speed in Declaration* on the alignment indicator. The coefficient of *Aligned Governor* is negative and significant and it shows that the wind speed of the least-affected county included in a declaration is, on average, about 15 km/h lower in aligned states. To provide a test for the overall probability of declaration changing when a state is aligned (the extensive margin), we run our main regression at the state level, using maximum *Wind Speed* in the state-year interacted with the alignment indicator. Appendix Figure H11 displays this result. As expected, the marginal effects curve is flatter and not significant.

Table 3: **Regression Results – Intensive Margin**

Dep. var.: <i>Lowest Wind Speed in Declaration</i>	(1)	(2)	(3)
<i>Aligned Governor</i>	-15.994 (7.290)	-15.379 (7.613)	-15.502 (5.655)
<i>Aligned Representative</i>			2.865 (5.891)
<i>Aligned Senators</i>			-14.140 (5.252)
<i>Rainfall & Storm Surge</i> controls		X	X
Socioeconomic controls			X
Maximum <i>Wind Speed</i> in State-Year			X
Dep. var. mean	41.573	41.573	39.312
Observations	227	227	212

The table displays regression coefficients with two-way clustered standard errors on the state and year level in parentheses. All estimations use the linear fixed effect-within estimator and include state and year fixed effects. Observations are aggregated at the state-year level. The dependent variable *Lowest Wind Speed in Declaration* captures the *Wind Speed* from the county with the lowest wind intensity that has been included in a declaration in a specific state-year. Columns 2 and 3 use *Rainfall* and *Storm Surge* as control variables. Column 3 adds the set of lagged socioeconomic covariates (*Population*, *Black Population*, *Real Income*, and *Per Capita Real Income*). We exclude the ten observations where only a single county was assigned a disaster declaration in a state-year. The sample runs from 1965–2018 in all regressions.

This result points at an intensive-margin channel of the political bias in situations that leave political actors with the most leeway: if it is unclear whether to include a county in a disaster declaration because it 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.³⁰

5.3 Sensitivity and Robustness

Before analyzing further heterogeneities of the political mechanism, we study the robustness of our main result. 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 H9. 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 3 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

³⁰The 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 H12, we provide correlational evidence in line with their findings. This is 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.

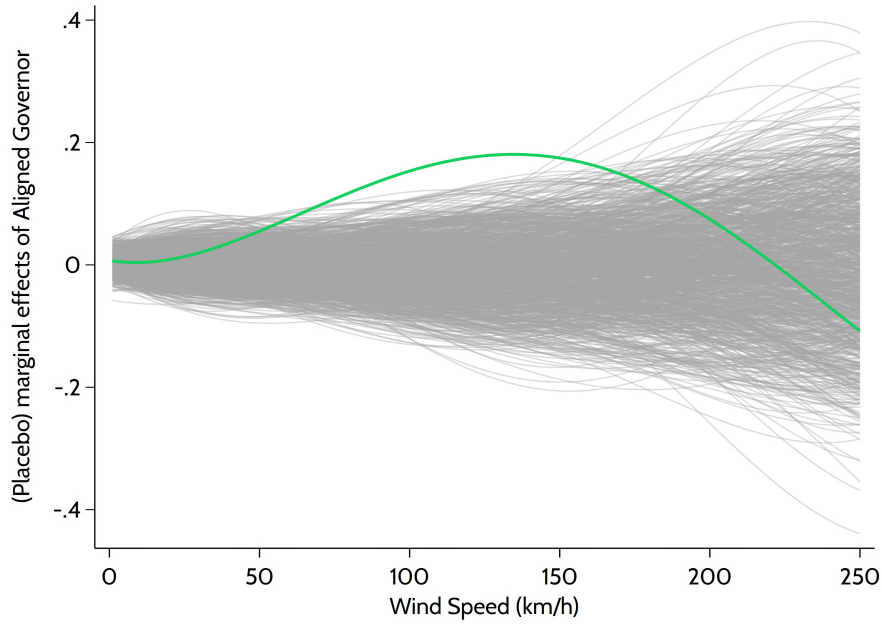


Figure 3: **Randomization Inference**

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 alignment status to all observations from a state-year, and we keep the total number of aligned years per state as in the original data. Appendix Figure H13 shows a graphical representation of the permutation p -value ($p_{perm.} = N^{-1} \sum_{i=1}^N \mathbb{1}[|\beta| < |\beta_{i,placebo}|]$). Appendix Figure H14 documents robustness to an even more conservative version of this test, reshuffling the full annual treatment patterns by years.

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. Appendix E).

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 :

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

We hence obtain a permutation p -value for every *Wind Speed* level and can derive the 95% confidence interval therefrom (see Appendix Figure H13). Based on this randomization inference approach, *Aligned Governor* has a positive and significant effect in the *Wind Speed* interval [53, 174] km/h, which is very

close to the interval [50, 178] km/h that we received from applying conventional two-way clustering to the standard errors (see Figure 2).

Regarding the choice of our baseline specification, the results of the polynomial approach are qualitatively similar when using different polynomials. Appendix Figure H8 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 the set of fixed effects 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., Brollo & 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 unaligned with the president by a small margin.³¹ Figure 4 displays the results for different bandwidths of close election outcomes. The results turn negative and significant for extremely high wind speeds in Panel [c]. In Panel [d], the confidence interval for high wind speeds is wider. 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 5 shows that the relationship tends to be stronger for governors with narrower margins

³¹In 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.

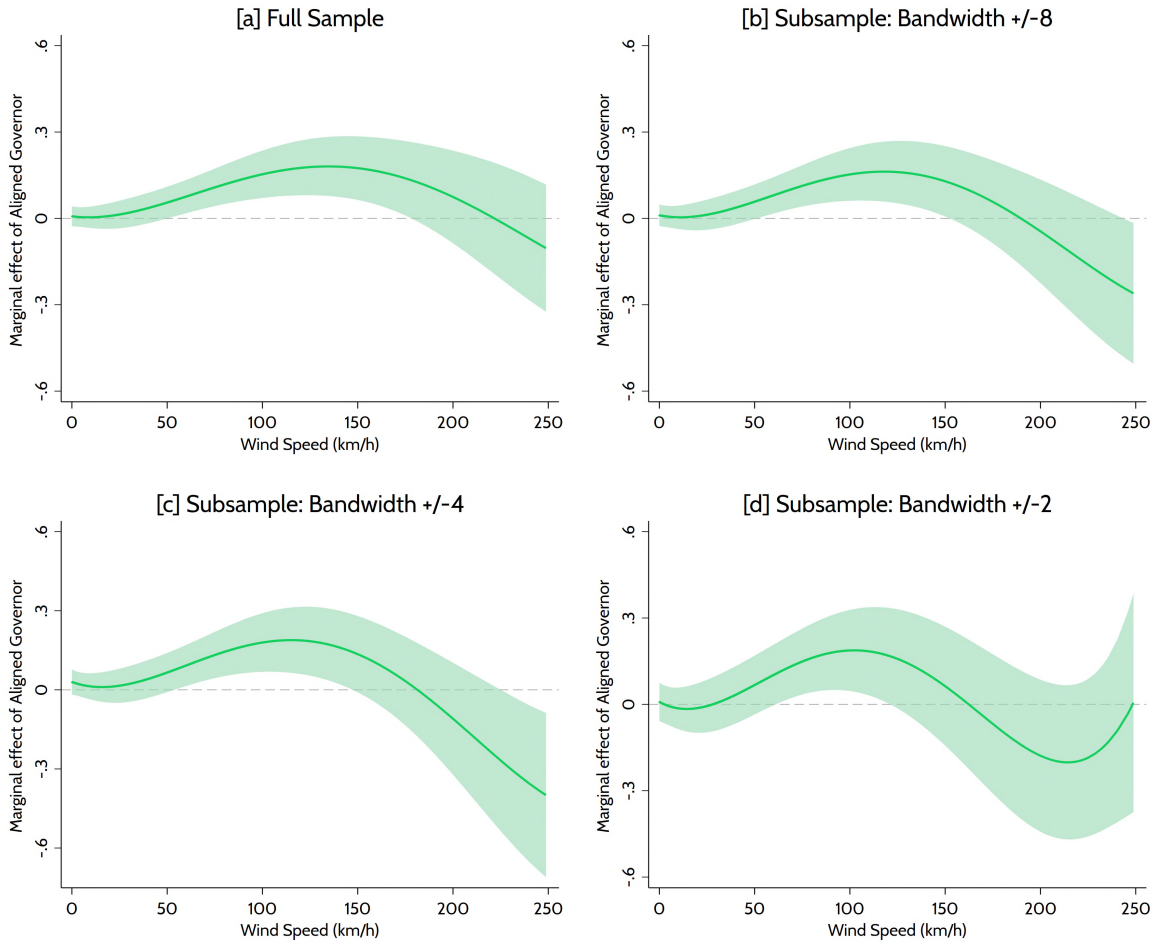


Figure 4: **Robustness: Close Elections Subsamples**

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.

of victory. The alignment effect is more pronounced and is significant in a broader *Wind Speed* range for governors who faced more competitive elections.³²

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 18 regressions, each excluding all observations from one individual state at a time. Panel [a] of Appendix Figure H16 exhibits that dropping individual states in no case results in a major difference from 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 (Panel [b]).

³²In Appendix Figure H15, 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.

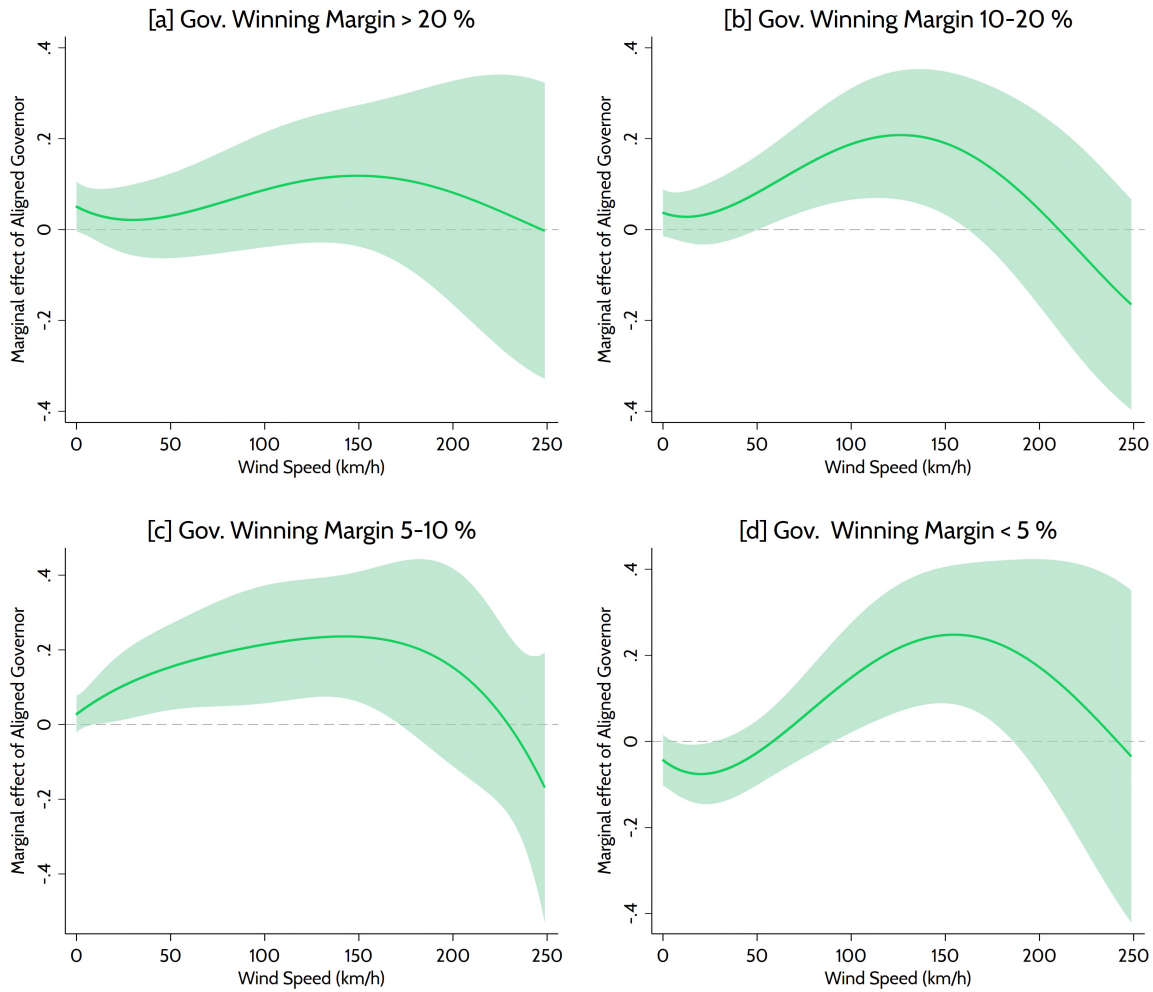


Figure 5: **Alignment Effects for Governors with Different Margins of Victory**

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.

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 H17), 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 this declaration type is issued 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 H18) does not change the results. Appendix Figures H19–H22 show further robustness tests regarding specification choice (H19), the flexible inclusion of further controls including non-hurricane declarations (H19, Panel [d]), party affiliation indicators, and other weather covariates (H20), as well as potential persistent

hurricane and declaration effects (H21), and sensitivity to outliers (H22). None of the robustness tests yields substantially different results or evidence against the existence of the alignment bias.

5.4 Additional Political Influences and Relief Cycles

The previous section documents the existence of an alignment bias in the allocation of disaster declarations for medium hurricane intensities and its robustness. To complement and refine this analysis, we examine heterogeneities and further sources of political influence.

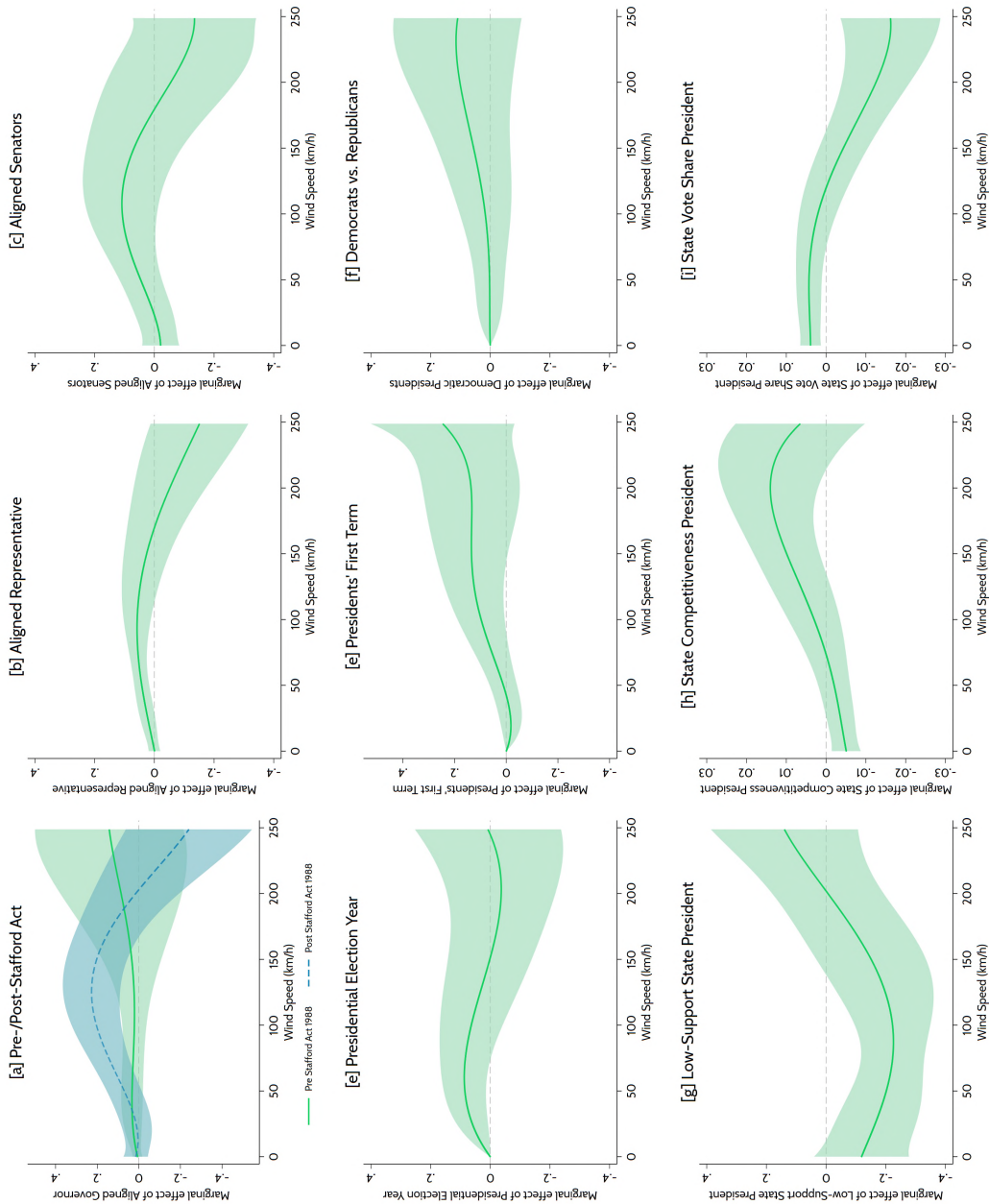
As we explain in Section 2.1 and Appendix A.1, the disaster declaration process is in place since the 1950s. The presumably most important change in disaster relief legislature was the passage of the Stafford Act in 1988. Arguably, the Stafford Act widened the president's discretionary power in the declaration process and expanded the types of eligible disasters and assistance programs (cf. Appendix A, Lindsay & McCarthy, 2015; Reeves, 2011; Sylves, 2008). Previous research suggests that the passage of the Stafford Act led to an increased politicization of disaster relief (Garrett & Sobel, 2003; Reeves, 2011). For instance, in a state-level analysis of presidential disaster declarations for the 1981–2004 period, Reeves (2011) finds that electorally more competitive states receive significantly more declarations but that this relationship only exists after 1988. In line with this observation, Figure 6, Panel [a] shows estimation results for the pre- and the post-1988 period. The alignment effect is only significant in post-Stafford Act years and weakly positive and insignificant before. As the Stafford Act strengthened the presidents' discretion to decide what qualifies for a declaration, this points to an intensified politically biased decision-making behavior exercised by the president. However, the same cautionary remarks as in previous studies apply. One should be careful not to draw premature conclusions from this finding because the Stafford Act coincides with the end of the Reagan administration and there might be other explanations for the differing declaration behavior of his successors (*ibid.*). For instance, the overall number of declarations is also much higher post-1988. An additional hurricane-specific caveat is that the 1980s largely featured comparably less active hurricane seasons than the following decades.

In addition to political alignment with state governors, 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 6, Panels [b] and [c]).³³

³³In Appendix Figure H23, 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.

Figure 6: Heterogeneous Political Effects

The figure displays marginal effects for the variables of interest depicted on the vertical axes from nine polynomial regressions. The shaded areas represent 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level. Panel [a] shows results from our main regression for the two subsamples before/after the Stafford Act in 1988. The other specifications add the depicted variable of interest as well as its interactions with the *Wind Speed* polynomial to our baseline for the estimation of heterogeneous effects. In Panels [d] and [e] *Presidents' First Term* and *Presidential Election Year* are indicators for a president's first term and presidential election years, respectively. Panel [f] shows the difference between Democratic and Republican presidents. In Panel [g] *Low-Support State President* is an indicator that takes the value 1 if the incumbent president received less than 40% of the statewide two-party vote share in the previous presidential election. *State Competitiveness President* in Panel [h] is the vote share of the candidate winning second-most statewide votes in the last presidential election (maximum competitiveness of 50 if the two top candidates received the same number of votes; 0 if one candidate received all the votes). Panel [i] depicts the marginal effect of the incumbent president's *State Vote Share* in the last election.



In Panels [d]–[f] of Figure 6, we analyze whether there is a significantly different declaration probability in years that are more meaningful from an electoral perspective and for the two major parties. For presidential election years (Panel [d]) and years that fall in the first term of a president (Panel [e]), we find positive and significant effects only in a very narrow wind speed range.³⁴ In Panel [f] we show the results from interactions with an indicator for democratic presidents. The differences in declaration behavior between Republicans and Democrats are insignificant in this analysis.

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 examine this, we start by interacting a dummy variable *Low-Support State (President)* with the wind speed polynomial.³⁵ Panel [g] indicates that counties in *Low-Support States*, ceteris paribus, have a significantly lower probability of receiving a declaration for low and intermediate storm intensities. This is in line with our expectations since the electoral incentives to “invest” political capital in these counties by issuing a borderline declaration are low. The president does not have a realistic chance of winning this state’s electoral votes in the next election. To move beyond interactions of the wind speed polynomial with binary variables, we apply a measure of electoral competitiveness based on Reeves (2011). *State Competitiveness* takes values between 0 (minimum competitiveness) and 50 (electoral battleground), measuring the two-party vote share of the candidate receiving the second-most statewide votes in the previous presidential election. Panel [h] displays the marginal effect of electoral competitiveness for different levels of wind speed. The results are positive and significant for the [135,213] km/h wind speed interval.

When we look at the president’s *State Vote Share* as an explanatory variable in Panel [i], the results are mixed. We find a slightly positive effect for weak wind speeds and a negative influence for extreme ones. We attribute these mixed results to the fact that a simple linear interaction is not sufficient to correctly capture the complexity of the relationships proposed by the two hypotheses mentioned above; e.g.,

³⁴These 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 7.

³⁵We code *Low-Support State (President)* as those where the incumbent president received less than 40% of the two-party vote share in the previous presidential election. In addition, Appendix H23, Panels [b]–[e] show results using congressional election results, where 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.

it is not clear from a electoral strategy point of view why to support high-support states more than battleground states.

However, it is certain that politicians at all levels need their electoral base to turn out and support them in election years. To conclude our analysis, we therefore analyze heterogeneities of the alignment effect with respect to electoral considerations in particular detail by using triple interactions. That is, we now interact the quartic *Wind Speed* polynomial with two political variables of interest at once; the alignment indicator and an additional electorally relevant factor depicted in the respective panel titles [a]–[d] of Figure 7.³⁶

Panel [a] of Figure 7 shows triple-interaction results by displaying the marginal effect of *Aligned Governor* for different levels of electoral support. Counties with higher electoral support for the president's and the aligned governor's party, benefit over-proportionally from the alignment bias. The co-partisans have a shared interest in pleasing their core supporters. Appendix Figure H24 shows the isolated triple interaction effect and demonstrates that the difference is statistically significant for medium wind speeds at the 95% confidence level.

Election years likely leverage the importance of the alignment bias as the key politicians have increased incentives to express their effort to the electorate and to co-campaign on successful provision of relief just before an election. Panel [b] of Figure 7 distinguishes alignment effects by *Presidential Election Year*. Panel [c] 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 for election years than for non-election years. However, Appendix Figure H24 shows that the difference between both curves in Panel [c] is not significant at the 95% confidence level.

In addition to such political budget cycles between years, there might also exist cycles within years. 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. If the political bias is (partly) electorally motivated, it is potentially stronger for storms occurring later in the season – but this should only play a role in election years. To test this, we additionally collected data on the month in which the strongest hurricane-related *Wind Speed* occurred in each county and year. Panel [d] shows the marginal effects of the linear *Hurricane Month* variable for different levels of *Wind Speed* distinguished for election years (dashed blue line) and non-election years (solid green line). In non-election years, the estimated effect of *Hurricane Month* is low for all wind speeds and mostly insignificant. In election years, however, it is positive and significant for a wide range of storm

³⁶For the regression displayed in Panel [a] of Figure 7, for instance, we add the expression $\sum_{b=1}^4 (Wind\ Speed_{i,t}^b \times Aligned\ Governor_{s,t} \times County\ Vote\ Share_{i,t})$ to the estimation equation, jointly with all the relevant two-way-interactions and main effects of the respective variables. Panels [b]–[d] proceed analogously for *Election Year* and *Hurricane Month*, including all factors that are not captured by the fixed effects.

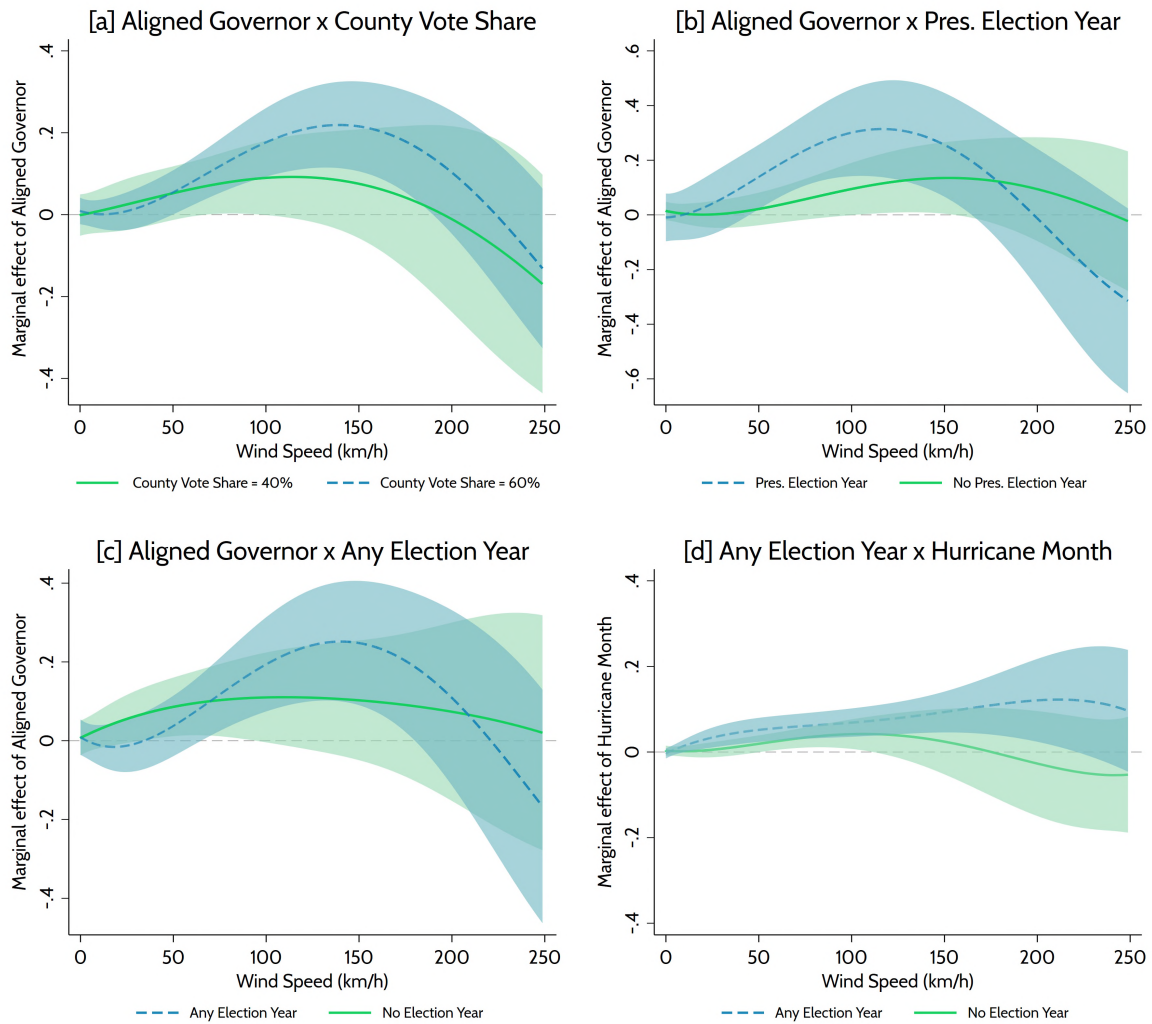


Figure 7: **Political Relief Cycles – Marginal Effects from Triple Interactions**

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 high-support counties (incumbent president’s county vote share of 60%) versus the effect in low-support counties indicated by the green solid line (county vote share of 40%). In Panel [b] 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 [c] 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 [d] the dashed blue line shows the effect of *Hurricane Month* in election years. The green solid line displays the estimated effect of *Hurricane Month* if *Any Election Year* equals 0. Appendix Figure H24 plots the marginal effects of the differences of the two curves in all four panels.

intensities. That is, hurricanes of equal intensity have a higher probability of being declared a disaster if they occur in a later month, but this relationship is only statistically significant 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.

Overall, our results contribute to the perception that there exists a political 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 data set and focusing on hurricane-related disaster declarations in the United States from 1965–2018. Applying flexible interaction models, we show that the issuance of disaster declarations involves a strongly heterogeneous political alignment bias. For extremely weak and strong hurricane intensities, there is no evidence for a political bias. For ambiguous decision situations, after medium-intensity hurricanes, we estimate that counties with a governor from the president's party have an up to 18 percentage points higher probability of receiving a federal disaster declaration. This heterogeneous political bias explains about 10% of total hurricane relief expenditure. We present evidence that the bias operates at the intensive margin, i.e., the marginal county covered by a declaration features lower hurricane intensity, on average, in "aligned declarations." 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. We need to remain careful about attributing the effect to the president as a single political actor since we observe the outcomes of the declaration process as a whole. However, the president has the final say in this process and we find empirical indications that the bias stems from the presidents' discretion in their decision-making. Our sub-analyses suggest that the passage of the Stafford Act, which augmented presidential discretion, led to a significant politicization of disaster relief allocation in the recent 30 years. Still, our data do not allow to finally disentangle "demand" (from the governors) and "supply side" effects (from the presidents) that lead to the alignment bias, so future research should focus on delivering further insights into the specifics of the mechanism.

The results from our analysis show the necessity of accounting for possible effect heterogeneities in analyses of individual decision-making processes. It is important to go beyond simple average estimates in such situations that involve diverse degrees of ambiguity regarding the appropriate decision or behavior. By disregarding the complexity of political-economic relationships in statistical estimations, the actual nexuses remain potentially concealed and the economic consequences underestimated. In ambiguous situations, the political effect is about four times higher than what conventional average estimates would

suggest. 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 heterogeneous relationships. As the heterogeneous effects are substantial and persistent with regard to disaster assistance, future research should evaluate whether our findings are generalizable to discretionary decision-making in other political-economic contexts. 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 whether, 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 current 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](#)).

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. [Deryugina & Kirwan \(2018\)](#) show empirically that higher bailout expectations reduce U.S. farmers' private crop insurance efforts and [Kousky et al. \(2018\)](#) demonstrate that U.S. households reduce their quantity of flood insurance if they received federal disaster assistance in the previous year.

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 and to assign declaration authority to a suitable and skilled bureaucrat, comparable to a central banker, who does not have to run for reelection (cf. [Alesina & Tabellini, 2007](#); [Bostashvili & Ujhelyi, 2019](#); [Enikolopov, 2014](#); [Hessami, 2018](#)).

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.

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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). From 2009–2018, FEMA spent on average about USD 8 billion in an average year.³⁸

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. In 2003 FEMA became part of the Department of Homeland Security (FEMA, 2017a). The Robert T. Stafford Disaster Relief and Emergency Assistance Act (PL 100-707) from 1988 constitutes the current legislation for federal disaster relief. Its passage strengthened the president’s position to make discretionary decisions in determining what qualifies a catastrophic situation to require federal relief (cf. Appendix Section A.2). It also 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 and local capacities first. Most natural disasters can be

³⁸See <https://www.washingtonpost.com/us-policy/2019/04/22/taxpayer-spending-us-disaster-fund-explodes-amid-climate-change-population-trends/>, last accessed September 3, 2021.

handled successfully without federal intervention by local or state means and the help of voluntary or non-governmental organizations. If the governor detects that the state and the local resources are insufficient to provide an effective response, they can initiate a preliminary damage assessment (PDA), thereby providing a first estimate of damages and unmet needs at the local level (FEMA – EMI, 2017; McCarthy, 2014). 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 (FEMA – EMI, 2017, Sylves, 2008, pp. 83–84).

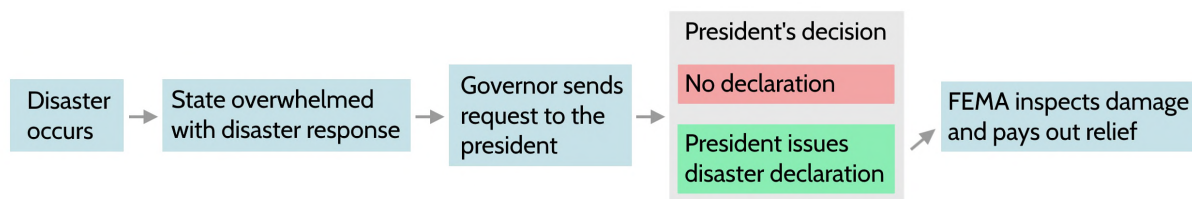


Figure A1: **The Disaster Declaration Process**

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 or when they deny a request; this fact has been emphasized by the Stafford Act (Reeves, 2011; Sylves, 2008). As the Stafford Act does not contain a narrow definition of eligible events, it authorizes presidents to issue emergency or major disaster declarations in case of any natural catastrophic event for which they determine that federal relief is necessary because local and state capacities are insufficient (Gasper, 2015; Lindsay & McCarthy, 2015; Sylves, 2008).³⁹ 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).⁴⁰ 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

³⁹Presidents 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).

⁴⁰Sylves (2008, p. 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).

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.

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 on the DRF, see Schroeder (2018).

B A Model of Presidential Disaster Declarations

B.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.⁴¹ The model focuses on the presidents' decision-making. Presidents have the declaration decisions at their disposal and therefore it ultimately hinges on their behavior whether we observe a politically biased outcome. We derive 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.⁴² The fact that decisions regarding the issuance of disaster declarations are in principle directly observable by the public 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 $X_i \in [-\frac{1}{2}\omega; \frac{1}{2}\omega]$.⁴³ More negative values of X_i denote a stronger ideological bias of voters toward the party of the president.

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

⁴¹As disaster relief is non-programmatic and connected to individual past events, we concentrate on retrospective voting. Regarding social transfers in general, voters react to both past spending (e.g., [De La O, 2013](#); [Levitt & Snyder, 1997](#); [Manacorda et al., 2011](#)) and future promises ([Elinder et al., 2015](#)).

⁴²The extension in Appendix B.3 discusses different levels of national public attention.

⁴³Assuming a uniform distribution on a sufficiently wide ideology interval facilitates the derivation of the alignment bias. Appendix B.3 discusses how different single-peaked voter distributions and densities – representing different levels of electoral competitiveness – affect the strength of the alignment bias.

behaves “attentively” and rewards politicians in elections for a vigorous disaster response, including federal disaster relief spending (cf. also [Bechtel & Hainmueller, 2011](#); [Cole et al., 2012](#); [Healy & Malhotra, 2009](#)). We incorporate these reactions by integrating disaster damage and relief in the voters’ private utility functions u_i with $u'_i > 0$ and $u''_i < 0$:

$$u_i \left(-b(s_j) \cdot (1 - D_j \cdot \psi) - \tau \right). \quad (3)$$

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 $\tau = N^{-1} \sum_{l=1}^N (D_l \cdot \psi b(s_l))$.⁴⁴ 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

$$u_i \geq X_i. \quad (4)$$

In practice, presidents face conflicting incentives when declaring a disaster in an unaligned county. It is unlikely that they willingly offer a stage to the requesting governor from the opposing party to claim the benefits of disaster relief. However, they would also want to benefit from the electoral reward of a declaration themselves. We account for these diametric incentives by adding the parameter θ , which alters the equation of electoral support to:

$$(1 - \theta)u_i \geq X_i + \theta u_i \quad (\text{where } \theta \in [0, 0.5]). \quad (5)$$

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., 2022](#); [Zudenkova, 2011](#)). Hence, in the aligned case, the expression simplifies to Equation (4), and the president’s party captures the entire electoral benefit from a declaration. In the unaligned case ($\theta > 0$), the president’s political benefits from a declaration are relatively lower since the opposite party governor can, for instance, try to campaign on the same issue.⁴⁵

⁴⁴A 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.3 explains how a higher importance of fairness considerations and the strength of the national public opinion can decrease the extent of the alignment bias.

⁴⁵[Arulampalam et al. \(2009\)](#) and [Solé-Ollé & Sorribas-Navarro \(2008\)](#) call the resulting effect of $\theta > 0$ “vote leakage”, where some share of the voter goodwill is captured by the opposite party. In our example, this might occur as the voters

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

$$\hat{X}_i^A = u_i \geq X_i \quad (6)$$

$$\hat{X}_i^U = (1 - 2\theta)u_i \geq X_i. \quad (7)$$

\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.

B.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:

$$\max_{D_j^A, D_j^U} \sum_{j=1}^{N^A} \Phi_m(\hat{X}_i^A) + \sum_{j=1}^{N^U} \Phi_n(\hat{X}_i^U), \quad (8)$$

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.⁴⁶ 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

also attribute some share of their utility gain from a declaration to the local governor's effort (cf. [Curto-Grau et al., 2018](#); [Geys & Vermeir, 2014](#)). As we assume that local governors only care about the utility of their own constituents, they would 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 president's party losing votes from a declaration) would imply reversed incentives for the president as the marginal utility of declarations becomes negative in unaligned counties ([Solé-Ollé & Sorribas-Navarro, 2008](#)).

⁴⁶ $\Delta \Phi_j^A = \omega^{-1} \left(u_i(D_j = 1, s_j) - u_i(D_j = 0, s_j) + \sum_{l=1, l \neq j}^N (1 - 2\theta_l)(u_l(D_j = 1, s_j) - u_l(D_j = 0, s_j)) \right) = 0$ 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.3 for a discussion of potential corner solutions of the model.

critical threshold s^* , however, differs between aligned (A) and unaligned (U) counties.⁴⁷ Presidents receive a higher reward for issuing a declaration for the same hurricane intensity in aligned counties compared to unaligned counties because of the lower political incentives represented by $\theta > 0$. Therefore, $s^{*U} > s^{*A}$ is required so that $\Delta\Phi^A = \Delta\Phi^U = 0$ holds with any $0 < \theta < 0.5$. 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.

$$D_j^* = \begin{cases} 1 & \text{if } s_j > s^{*U} \\ 1 & \text{if } s^{*U} \geq s_j > s^{*A} \wedge \theta = 0 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

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 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.3 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 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.

B.3 Further Theoretical Considerations

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

$$\text{FOC's: } \Delta\Phi_j^A = \Delta\Phi_j^U = 0$$

⁴⁷Gaspar (2015) discusses a related “threshold hypothesis,” where presidents have different implicit declaration thresholds in election years and depending on a state's electoral competitiveness. Our analysis builds up on this idea and extends it by showing that there is not only a static bias between, e.g., election years and non-election years, but that the degree to which political constellations influence politicians' decision-making varies within years and locations depends on disaster intensity.

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

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.⁴⁸ 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, 2020](#); [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 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 (6) and (7) in Appendix B.1 become

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

⁴⁸An additional assumption for the voter ideology distribution is that ω is sufficiently large so that $\hat{X} \in [-\frac{1}{2}\omega, \frac{1}{2}\omega]$.

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

$$\begin{aligned} \Delta \Phi_j^A(s^{*A}) + \sum_{l=1, l \neq j}^N f_l(s^{*A}, \alpha) &< \Delta \Phi_j^U(s^{*U}) + \sum_{l=1, l \neq j}^N f_l(s^{*U}, \alpha) \\ \Rightarrow s_F^{*A} > s^{*A} \vee s_F^{*U} < s^{*U} \\ \Rightarrow s_F^{*U} - s_F^{*A} < s^{*U} - s^{*A} \end{aligned}$$

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 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, 2021). As Gallagher (2021) 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.

D Hurricanes

Hurricanes constitute the most severe and destructive class of storms.⁴⁹ A hurricane is a cyclonically rotating atmospheric low-pressure system with a typical diameter of the order of 500–700 km (Aguado & Burt, 2015, p. 384, Korty, 2013, pp. 481–485, Terry, 2007). 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.⁵⁰ 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). As soon as it makes landfall the storm weakens quickly.

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

⁴⁹As 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).

⁵⁰This 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 third damage source of hurricanes is storm surge. It affects coastal areas and depends, among others, on the wind speed intensity, the coastal geography, the bathymetry, and the tidal cycle. Appendix E explains how we account for the different impacts of tropical cyclones.

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.

E Hurricane Data

Wind Speed

To generate a proxy for hurricane damages, we adopt the tropical cyclone data assembled by [Kunze \(2021\)](#) 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

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

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

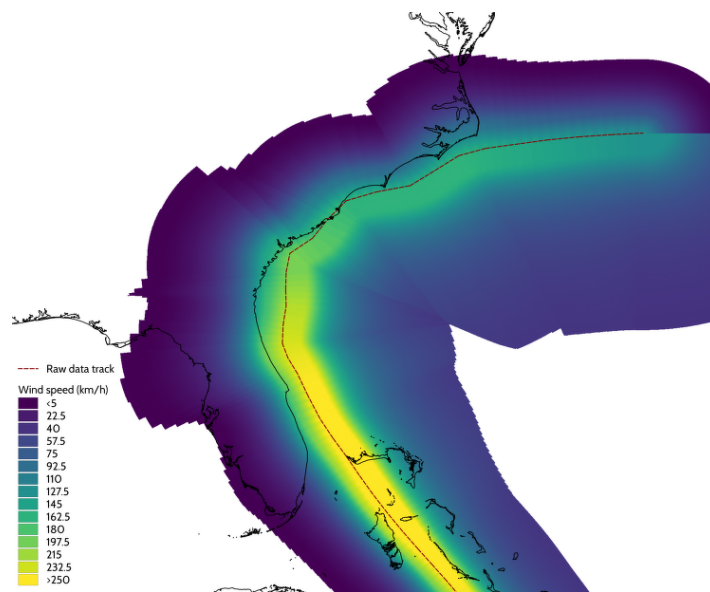


Figure E1: **Wind Field Model and Raw Data Track of Hurricane Matthew, 2016**

The figure displays asymmetric wind fields from our hurricane model for Hurricane Matthew. The color gradient indicates wind speed intensities. The red dotted line corresponds to the IBTrACS raw data track.

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 E1 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 E2 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.

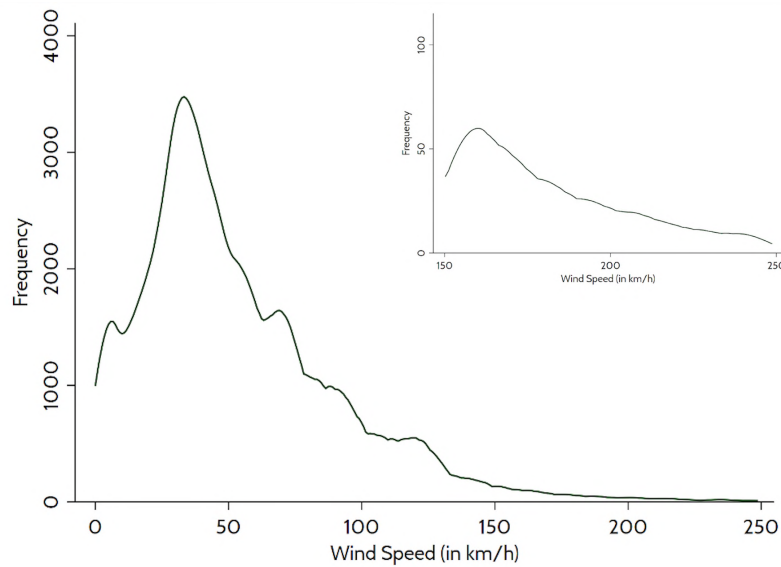


Figure E2: **Distribution of Hurricane *Wind Speed* >0, 1965–2018**

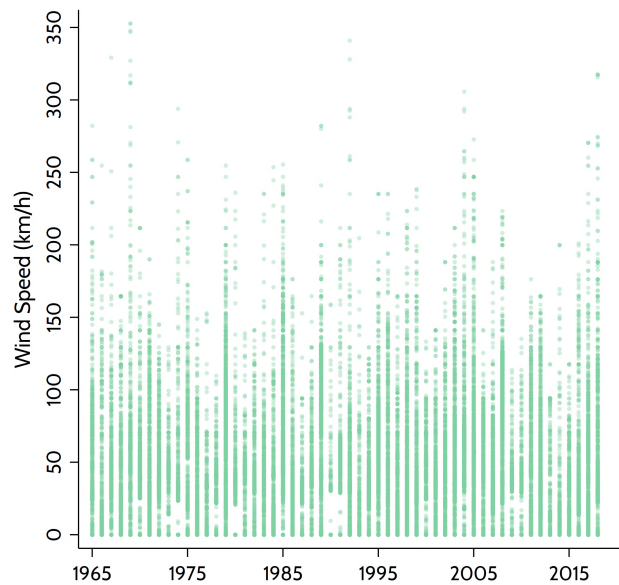


Figure E3: **Yearly Variation of Maximum *Wind Speed* per County, 1965–2018**

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

Appendix Figure E3 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.⁵¹

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.

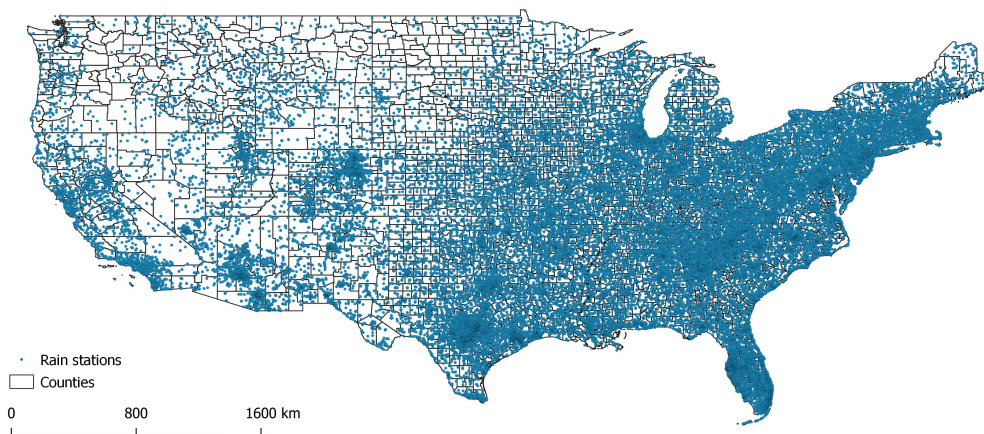


Figure E4: **Distribution of Weather Stations for Hurricane Rainfall Data**

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.⁵² 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 &

⁵¹As a robustness test, we replace our *Wind Speed* polynomial with the damage function proposed by Emanuel (2011) (Figure H18, Panel [b]). He proposes specific wind speed thresholds above which a certain percentage of physical damage occurs or 50% of the physical infrastructure is destroyed. Consequently, for each hurricane s in county i , we calculate the following damage index: $Damage_{is} = \frac{v_{is}^3}{1+v_{is}^3}$, where $v_{is} = \frac{\max[(S_{is}-S_{thresh}),0]}{S_{half}-S_{thresh}}$. S_{is} is the maximum wind speed of storm s in county i as calculated in equation 10. For this sensitivity test, we use the functional form assumption and calibration proposed by Emanuel (2011); 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}).

⁵²The data include precipitation that arises from the potential influence of weather fronts interacting with the tropical storm (Czajkowski et al., 2011; Knight & Davis, 2009).

Pielke Jr., 2001), we assume that the strongest rainfall event in a county has the highest likelihood of causing a declaration. We thus keep the strongest precipitation value from each county in each year.

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.

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 DELFT 3D 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 that 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 – V1 (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>Hurricane Damage Index</i>	Hurricane damage index proposed by Emanuel (2011). For each wind speed, the index assumes a certain fraction of property to be destroyed. See Appendix E for details.
<i>Low-Support State President</i>	Indicator variable taking the value 1 if the incumbent president obtained less than 40% of the statewide vote share in the most recent presidential election, and 0 otherwise.

<i>State Competitiveness President</i>	Vote share of the second-strongest candidate in a state in the last presidential election. 0 = least competitive (one candidate receiving all the votes); 50 = maximum competitive (the two strongest candidates receiving the same number of votes).
<i>State Vote Share President</i>	Statewide vote share of the incumbent president in the last presidential election in %.
<i>County Vote Share President</i>	Statewide vote share of the incumbent president in the last presidential election in %.
<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>Swing State President</i>	Indicator for states in which the party winning the majority of the votes changed in at least one of the last three elections.
<i>Swing State Governor</i>	Indicator for states in which the party appointing the governor changed in at least one of the last three elections.
<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>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>District Competitiveness</i>	Vote share of the second-strongest candidate in a district in the last congressional election. 0 = least competitive (one candidate receiving all the votes); 50 = maximum competitive (the two strongest candidates receiving the same number of votes).
<i>District Vote Share</i>	District vote share of the candidate from the incumbent president's party in the most recent congressional election in %.
<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/ .
<i>Real 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>Per Capita Real Income (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>	49,092	0.11	0.31	0.00	1.00
<i>Emergency Declaration</i>	49,092	0.05	0.22	0.00	1.00
<i>Major Declaration</i>	49,092	0.09	0.29	0.00	1.00
<i>Declarations</i>	49,092	0.15	0.50	0.00	5.00
<i>Aligned Governor</i>	49,092	0.44	0.50	0.00	1.00
<i>Aligned Representative</i>	49,092	0.46	0.50	0.00	1.00
<i>Aligned Senators</i>	49,092	0.30	0.46	0.00	1.00
<i>Alignment Count</i>	49,092	1.89	1.28	0.00	4.00
<i>Wind Speed</i>	49,092	34.55	41.77	0.00	352.71
<i>Rainfall</i>	49,092	69.46	78.48	0.00	1,538.73
<i>Storm Surge</i>	49,092	0.07	0.35	0.00	6.01
<i>Wind Speed Count</i>	49,092	1.00	1.07	0.00	7.00
<i>Rainfall Count</i>	49,092	2.06	1.48	0.00	8.00
<i>Hurricane Month</i>	48,808	8.26	1.39	5.00	11.00
<i>Mean Annual Rainfall</i>	49,044	1,201.74	336.73	69.22	2,885.00
<i>Mean Annual Temperature</i>	49,044	15.98	3.93	2.46	25.83
<i>Hurricane Damage Index</i>	49,092	0.01	0.06	0.00	0.93
<i>Low-Support State President</i>	49,034	0.03	0.17	0.00	1.00
<i>State Competitiveness President</i>	49,034	42.46	6.02	12.86	50.00
<i>State Vote Share President</i>	49,054	54.51	8.53	12.86	80.87
<i>County Vote Share President</i>	49,054	54.59	15.04	3.41	93.65
<i>High-Support District</i>	49,092	0.31	0.46	0.00	1.00
<i>Low-Support District</i>	49,092	0.40	0.49	0.00	1.00
<i>District Competitiveness</i>	49,092	26.43	16.46	0.00	49.99
<i>Presidential Election Year</i>	49,092	0.24	0.43	0.00	1.00
<i>Any Election Year</i>	49,092	0.56	0.50	0.00	1.00
<i>Presidents' First Term</i>	49,092	0.67	0.47	0.00	1.00
<i>Years President Runs for Reelection</i>	49,092	0.16	0.37	0.00	1.00
<i>Swing State President</i>	49,064	0.62	0.48	0.00	1.00
<i>Swing State Governor</i>	48,973	0.63	0.48	0.00	1.00
<i>County Vote Change (Pres.)</i>	47,118	-2.15	14.49	-71.98	88.32
<i>Population (log)</i>	49,026	10.51	1.36	3.69	15.36
<i>Black Population (log)</i>	45,654	8.23	2.17	0.00	13.80
<i>Real Income (log)</i>	43,909	13.80	1.57	7.72	19.52
<i>Per Capita Real Income (log)</i>	43,909	10.16	0.39	8.75	12.12

G Additional Tables

Table G1: **Robustness – Alternative Models**

Dep. var.: <i>Declaration(s)</i>	(1)	(2)	(3)	(4)
<i>Aligned Governor</i>	0.932 (0.052)	0.500 (0.028)	0.514 (0.025)	0.609 (0.165)
<i>Aligned Representative</i>	0.213 (0.047)	0.117 (0.025)	0.125 (0.029)	0.108 (0.069)
<i>Aligned Senators</i>	0.304 (0.054)	0.161 (0.029)	0.215 (0.033)	0.188 (0.234)
<i>Wind Speed (St. Dev.)</i>	1.115 (0.027)	0.607 (0.014)	0.472 (0.018)	0.471 (0.048)
<i>Rainfall (St. Dev.)</i>	0.781 (0.023)	0.420 (0.012)	0.188 (0.013)	0.231 (0.031)
<i>Storm Surge (St. Dev.)</i>	0.058 (0.086)	0.012 (0.045)	-0.088 (0.044)	-0.055 (0.041)
Model	logit	probit	Poisson	PPML
Dep. var. mean	0.121	0.121	0.156	0.174
Observations	43,295	43,295	48,346	43,295

The table displays regression coefficients for different estimation models with standard errors in parentheses. 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 are 40.59 km/h for *Wind Speed*, 79.04 mm for *Rainfall*, and 0.81 m for *Storm Surge*. “Dep. var. mean” denotes the mean of the dependent variable. The sample runs from 1965–2018 in all regressions.

Table G2: **Robustness – Socioeconomic Control Variables**

Dep. var.: <i>Declaration</i>	(1)	(2)	(3)	(4)	(5)	(6)
<i>Aligned Governor</i>		0.053 (0.019)	0.048 (0.018)	0.052 (0.019)	0.052 (0.019)	0.051 (0.019)
<i>Aligned Representative</i>			0.019 (0.007)	0.019 (0.008)	0.020 (0.008)	0.020 (0.008)
<i>Aligned Senators</i>			0.021 (0.022)	0.014 (0.029)	0.017 (0.029)	0.016 (0.029)
<i>Wind Speed (St. Dev.)</i>	0.090 (0.009)	0.090 (0.008)	0.090 (0.008)	0.088 (0.009)		
<i>Rainfall (St. Dev.)</i>	0.076 (0.006)	0.076 (0.006)	0.076 (0.006)	0.081 (0.006)	0.081 (0.006)	0.081 (0.006)
<i>Storm Surge (St. Dev.)</i>	0.020 (0.009)	0.020 (0.009)	0.020 (0.009)	0.021 (0.010)	-0.001 (0.010)	-0.001 (0.009)
<i>Population (log)_{t-1}</i>	0.091 (0.115)	0.133 (0.114)	0.137 (0.116)	0.051 (0.132)	0.045 (0.134)	0.054 (0.134)
<i>Black Population (log)_{t-1}</i>	-0.030 (0.009)	-0.031 (0.009)	-0.032 (0.009)	-0.034 (0.020)	-0.033 (0.020)	-0.031 (0.020)
<i>Real Income (log)_{t-1}</i>	-0.066 (0.116)	-0.107 (0.115)	-0.108 (0.117)	-0.004 (0.143)	-0.019 (0.144)	-0.032 (0.144)
<i>Per Capita Real Income (log)_{t-1}</i>	0.042 (0.114)	0.079 (0.113)	0.083 (0.115)	0.057 (0.148)	0.063 (0.148)	0.074 (0.148)
County × decade FE				X	X	X
<i>Wind Speed</i> polynomial					X	
<i>Wind Speed</i> bins						X
Alternative SE: <i>Aligned Gov.</i>						
State & year cluster		0.025	0.021	0.023	0.024	0.022
Spatial cluster		0.023	0.021	0.022	0.022	0.021
Dep. var. mean	0.112	0.112	0.112	0.112	0.112	0.112
Observations	42,958	42,958	42,958	42,958	42,958	42,958

The table displays regression coefficients with two-way clustered standard errors on the state × year and county level in parentheses. The number of clusters is 846 in the state-year dimension and 1,083 in the county dimension. 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 are 40.59 km/h for *Wind Speed*, 79.04 mm for *Rainfall*, and 0.81 m for *Storm Surge*. Models 4–6 replace county fixed effects with county × decade fixed effects. “*Wind Speed* bins” signifies the usage of the semi-parametric approach to model wind speed. “*Wind Speed* polynomial” indicates the usage of quartic polynomials. For the main variable of interest *Aligned Governor*, we show standard errors based on two alternative clustering adjustments below the regression results: two-way clustering on the state & year level and a spatiotemporal HAC-robust clustering with 1000 km and a 10 year cutoff. “Dep. var. mean” denotes the mean of the dependent variable. Due to the availability of county-level income data, the sample runs from 1970–2018 in all regressions.

Table G3: **Sequential F-Tests Polynomials**

	<i>F</i> -statistic	<i>p</i> -value
9 vs 8	0.0529494	0.9484309
8 vs 7	0.3794132	0.6843691
7 vs 6	2.096429	0.1234774
6 vs 5	1.562626	0.2101371
5 vs 4	1.029524	0.3575853
4 vs 3	3.750794	0.0238569
3 vs 2	9.227355	0.0001077

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*.

Table G4: Robustness – Alternative Clustering

Dep. var.: Declaration	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Aligned Governor</i>	0.044 (0.003)	0.044 (0.018)	0.044 (0.024)	0.044 (0.024)	0.044 (0.024)	0.044 (0.020)	0.044 (0.021)	0.044 (0.022)	0.045 (0.018)
<i>Aligned Representative</i>	0.021 (0.003)	0.021 (0.008)	0.021 (0.009)	0.021 (0.009)	0.021 (0.009)	0.021 (0.008)	0.021 (0.009)	0.021 (0.009)	0.023 (0.009)
<i>Aligned Senators</i>	0.018 (0.005)	0.018 (0.033)	0.018 (0.032)	0.018 (0.032)	0.018 (0.034)	0.018 (0.027)	0.018 (0.028)	0.018 (0.029)	0.020 (0.024)
<i>Wind Speed (St. Dev.)</i>	0.084 (0.002)	0.084 (0.005)	0.084 (0.014)	0.084 (0.014)	0.084 (0.012)	0.084 (0.010)	0.084 (0.010)	0.084 (0.011)	0.085 (0.011)
<i>Rainfall (St. Dev.)</i>	0.081 (0.002)	0.081 (0.008)	0.081 (0.007)	0.081 (0.007)	0.081 (0.010)	0.081 (0.006)	0.081 (0.006)	0.081 (0.007)	0.080 (0.006)
<i>Storm Surge (St. Dev.)</i>	0.024 (0.007)	0.024 (0.008)	0.024 (0.012)	0.024 (0.013)	0.024 (0.012)	0.024 (0.010)	0.024 (0.010)	0.024 (0.011)	0.024 (0.010)
Cluster	County	State	Year	County & Year	State & Year	Spatial, 500 km	Spatial, 750 km	Spatial, 1000 km	Hurricane
No. of clusters	1,136	18	54	1,136 & 54	18 & 54				303
Dep. var. mean	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.109
Observations	49,092	49,092	49,092	49,092	49,092	49,092	49,092	49,092	47,875

The table displays regression coefficients with standard errors clustered at different levels in parentheses for the estimation in column 4 in the main results table. All estimations use the linear fixed effect within estimator and include year fixed effects and county × decade fixed effects. *Wind Speed*, *Rainfall*, and *Storm Surge* are shown in standard deviation increases (above zero). Standard deviations are 40.59 km/h for *Wind Speed*, 79.04 mm for *Rainfall*, and 0.81 m for *Storm Surge*. “Cluster” lists the respective clustering adjustment for each column. Models 6-8 use a spatiotemporal HAC-robust clustering with a radius of 500/750/1000 km and a 10 year cutoff. “No. of Clusters” reports the number of clusters in the applied clustering dimensions. The number of observations is slightly lower for the “Hurricane cluster” because there is no unique storm identifier in our data for few storms systems that did only cause rainfall but no positive hurricane wind speed observation in our sample. “Dep. var. mean” denotes the mean of the dependent variable. The sample runs from 1965–2018 in all regressions.

Table G5: **Average Regression Results – Past Events**

Dep. var.: <i>Declaration</i>	(1)	(2)
<i>Aligned Governor</i>	0.036 (0.018)	0.044 (0.019)
<i>Aligned Representative</i>	0.016 (0.008)	0.023 (0.008)
<i>Aligned Senators</i>	-0.002 (0.028)	0.018 (0.030)
<i>Wind Speed (St. Dev.)</i>	0.082 (0.008)	0.088 (0.009)
<i>Rainfall (St. Dev.)</i>	0.073 (0.005)	0.081 (0.006)
<i>Storm Surge (St. Dev.)</i>	0.024 (0.010)	0.023 (0.010)
Lags	<i>Declaration</i>	<i>Wind Speed</i>
Alternative SE: <i>Aligned Gov.</i>		
State & year cluster	0.020	0.023
Spatial cluster	0.020	0.022
Dep. var. mean	0.107	0.107
Observations	49,092	49,092

The table displays regression coefficients with two-way clustered standard errors on the state × year and county level in parentheses. The number of clusters is 927 in the state-year dimension and 1,136 in the county dimension. All estimations use the linear fixed effect-within estimator and include year fixed effects and county × decade fixed effects. 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 are 40.59 km/h for *Wind Speed*, 79.04 mm for *Rainfall*, and 0.81 m for *Storm Surge*. For the main variable of interest *Aligned Governor*, we show standard errors based on two alternative clustering adjustments below the regression results: two-way clustering on the state & year level and a spatiotemporal HAC-robust clustering with 1000 km and a 10 year cutoff. “Dep. var. mean” denotes the mean of the dependent variable. The sample runs from 1965–2018 in all regressions.

Table G6: **Polynomial Regression Results of Main Specification**

Dep. var.: <i>Declaration</i>	(1)
<i>Wind Speed</i>	$8.156 \cdot 10^{-4}$ ($1.095 \cdot 10^{-3}$)
<i>Wind Speed</i> ²	$-1.938 \cdot 10^{-5}$ ($2.221 \cdot 10^{-5}$)
<i>Wind Speed</i> ³	$2.763 \cdot 10^{-7}$ ($1.325 \cdot 10^{-7}$)
<i>Wind Speed</i> ⁴	$-6.322 \cdot 10^{-10}$ ($2.323 \cdot 10^{-10}$)
<i>Rainfall</i>	$1.023 \cdot 10^{-3}$ ($7.153 \cdot 10^{-5}$)
<i>Storm Surge</i>	$5.259 \cdot 10^{-4}$ ($1.185 \cdot 10^{-2}$)
<i>Aligned Governor</i>	$7.358 \cdot 10^{-3}$ ($1.767 \cdot 10^{-2}$)
<i>Aligned Governor</i> × <i>Wind Speed</i>	$-8.225 \cdot 10^{-4}$ ($1.446 \cdot 10^{-3}$)
<i>Aligned Governor</i> × <i>Wind Speed</i> ²	$5.097 \cdot 10^{-5}$ ($3.084 \cdot 10^{-5}$)
<i>Aligned Governor</i> × <i>Wind Speed</i> ³	$-3.370 \cdot 10^{-7}$ ($1.970 \cdot 10^{-7}$)
<i>Aligned Governor</i> × <i>Wind Speed</i> ⁴	$5.558 \cdot 10^{-10}$ ($3.687 \cdot 10^{-10}$)
<i>Aligned Representative</i>	$2.073 \cdot 10^{-2}$ ($8.051 \cdot 10^{-3}$)
<i>Aligned Senators</i>	$2.287 \cdot 10^{-2}$ ($3.063 \cdot 10^{-2}$)
Dep. var. mean	0.107
Observations	49,092

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. The estimation uses the linear fixed effect-within estimator and includes year and county × decade fixed effects. “Dep. var. mean” denotes the mean of the dependent variable. The sample runs from 1965–2018.

Table G7: **Bins Regression Results of Main Specification**

Dep. var.: <i>Declaration</i>	(1)
<i>Wind Speed Bin 1</i>	0.0193 (0.0216)
<i>Wind Speed Bin 2</i>	0.0184 (0.0201)
<i>Wind Speed Bin 3</i>	0.0316 (0.0264)
<i>Wind Speed Bin 4</i>	0.0761 (0.0301)
<i>Wind Speed Bin 5</i>	0.1331 (0.0498)
<i>Wind Speed Bin 6</i>	0.1897 (0.0630)
<i>Wind Speed Bin 7</i>	0.4826 (0.0672)
<i>Wind Speed Bin 8</i>	0.5665 (0.0851)
<i>Wind Speed Bin 9</i>	0.5307 (0.1050)
<i>Wind Speed Bin 10</i>	0.7105 (0.0639)
<i>Rainfall</i>	0.0010 (0.0001)
<i>Storm Surge</i>	0.0001 (0.0117)
<i>Aligned Governor</i>	0.0111 (0.0162)
<i>Aligned Governor × Wind Speed Bin 1</i>	-0.0290 (0.0326)
<i>Aligned Governor × Wind Speed Bin 2</i>	0.0151 (0.0268)
<i>Aligned Governor × Wind Speed Bin 3</i>	0.0933 (0.0400)
<i>Aligned Governor × Wind Speed Bin 4</i>	0.1104 (0.0406)
<i>Aligned Governor × Wind Speed Bin 5</i>	0.1289 (0.0599)
<i>Aligned Governor × Wind Speed Bin 6</i>	0.2061 (0.0757)
<i>Aligned Governor × Wind Speed Bin 7</i>	0.0731 (0.0842)
<i>Aligned Governor × Wind Speed Bin 8</i>	0.0646 (0.1153)
<i>Aligned Governor × Wind Speed Bin 9</i>	0.1491 (0.1158)
<i>Aligned Governor × Wind Speed Bin 10</i>	-0.0500 (0.0861)
<i>Aligned Senators</i>	0.0225 (0.0304)
<i>Aligned Representative</i>	0.0204 (0.0080)
Dep. var. mean	0.107
Observations	49,092

The table displays regression coefficients of the main semi-parametric specification with two-way clustered standard errors on the state × year and county level in parentheses. The estimation uses the linear fixed effect-within estimator and includes year and county × decade fixed effects. “Dep. var. mean” denotes the mean of the dependent variable. The sample runs from 1965–2018.

Table G8: Declaration Turndowns and Relief Amounts

	<i>Declaration</i>	<i>Public Assistance Projects</i>	<i>Total Public Assistance per Capita (log)</i>
	(1)	(2)	(3)
<i>Aligned Governor</i>	-0.003 (0.005)	-8.162 (15.953)	0.236 (0.210)
<i>Aligned Representative</i>	0.001 (0.003)	-2.420 (9.615)	-0.046 (0.120)
<i>Aligned Senators</i>	0.002 (0.005)	11.233 (15.914)	-0.327 (0.188)
<i>Wind Speed polynomial</i>	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 polynomial*” 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. Note that the results in column 1 have to be interpreted with caution since the governor’s decision to request a declaration is itself endogeneous to the process. The closer the declaration process is to a perfect information scenario, the more preemptive obedience we would expect. 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).

Table G9: Regression Results – Balance Test

	<i>Population (log)_{t-1}</i>	<i>Real Income (log)_{t-1}</i>	<i>Per Capita Real Income (log)_{t-1}</i>	<i>Black Population (log)_{t-1}</i>	<i>Aligned Governor</i>
	(1)	(2)	(3)	(4)	(5)
<i>Wind Speed (St. Dev.)</i>	0.005 (0.004)	0.006 (0.004)	-0.000 (0.002)	-0.002 (0.006)	0.001 (0.014)
Dep. var. mean	10.503	13.789	10.153	8.215	0.439
Observations	49,020	43,088	43,088	44,804	49,092

The table demonstrates the exogeneity of hurricanes showing conditional correlations of *Wind Speed* with socioeconomic factors and the alignment indicator. It displays regression coefficients with two-way clustered standard errors on the state \times year and county level in parentheses. The dependent variable is indicated in the respective column title. All estimations use the linear fixed effect-within estimator and include county and year fixed effects. *Wind Speed* is shown in standard deviation increases (above zero), where one standard deviations is 40.59 km/h. “Dep. var. mean” denotes the mean of the dependent variable.

H Additional Figures

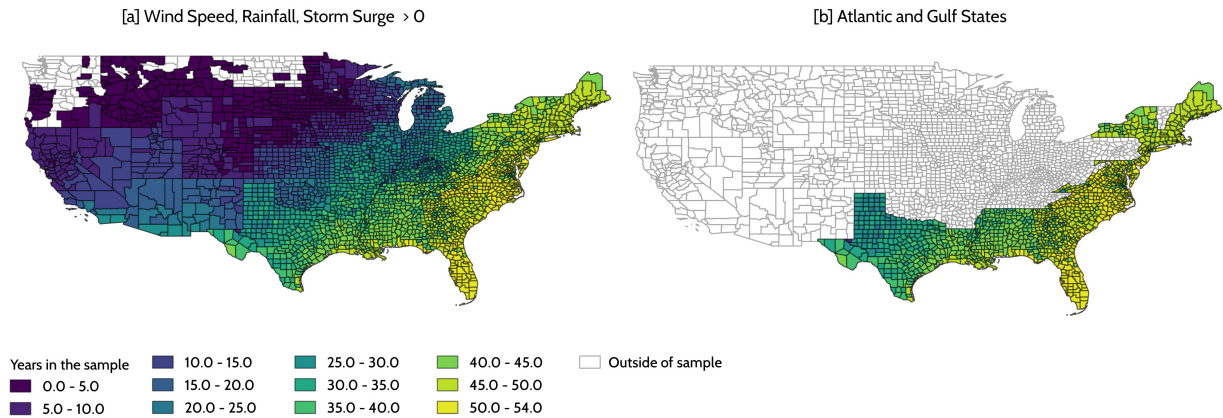


Figure H1: Sample Comparison – Years with Storm Observations

This figure displays the number of years in which counties have been affected by tropical cyclone-related *Wind Speed*, *Rainfall*, or *Storm Surge*. Panel [a] includes all counties with either a positive *Wind Speed*, *Rainfall*, and *Storm Surge* observation. Panel [b] represents our baseline sample, covering only counties within states with an Atlantic or Gulf of Mexico coastline. We show robustness tests using the sample in Panel [a] but since non-coastal states are usually only treated with low storm intensities and in few years, our baseline results focus on Panel [b].

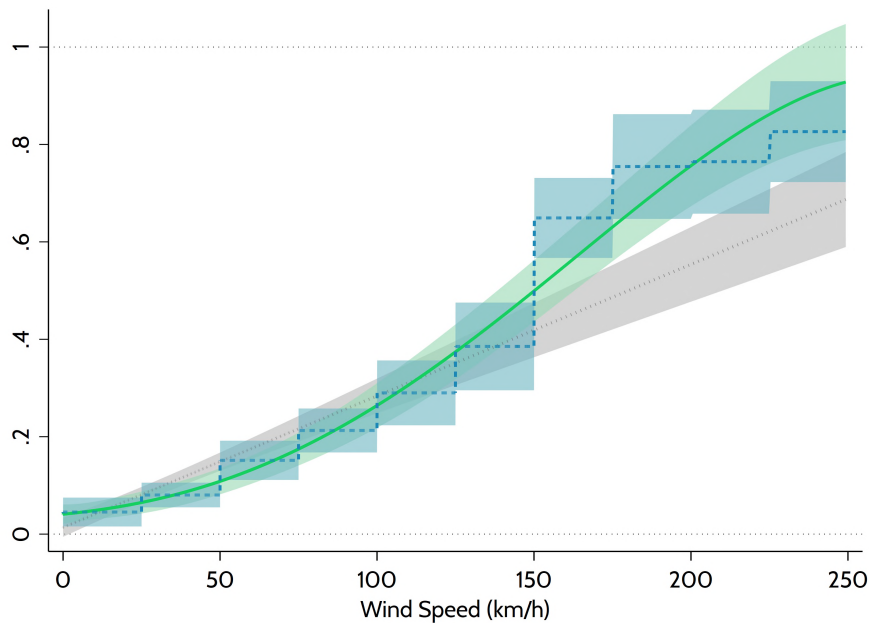


Figure H2: Relationship of Wind Speeds and Disaster Declarations

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 county \times decade fixed effects. The shaded areas show 95% confidence intervals based two-way clustered standard errors on the state \times year and county level.

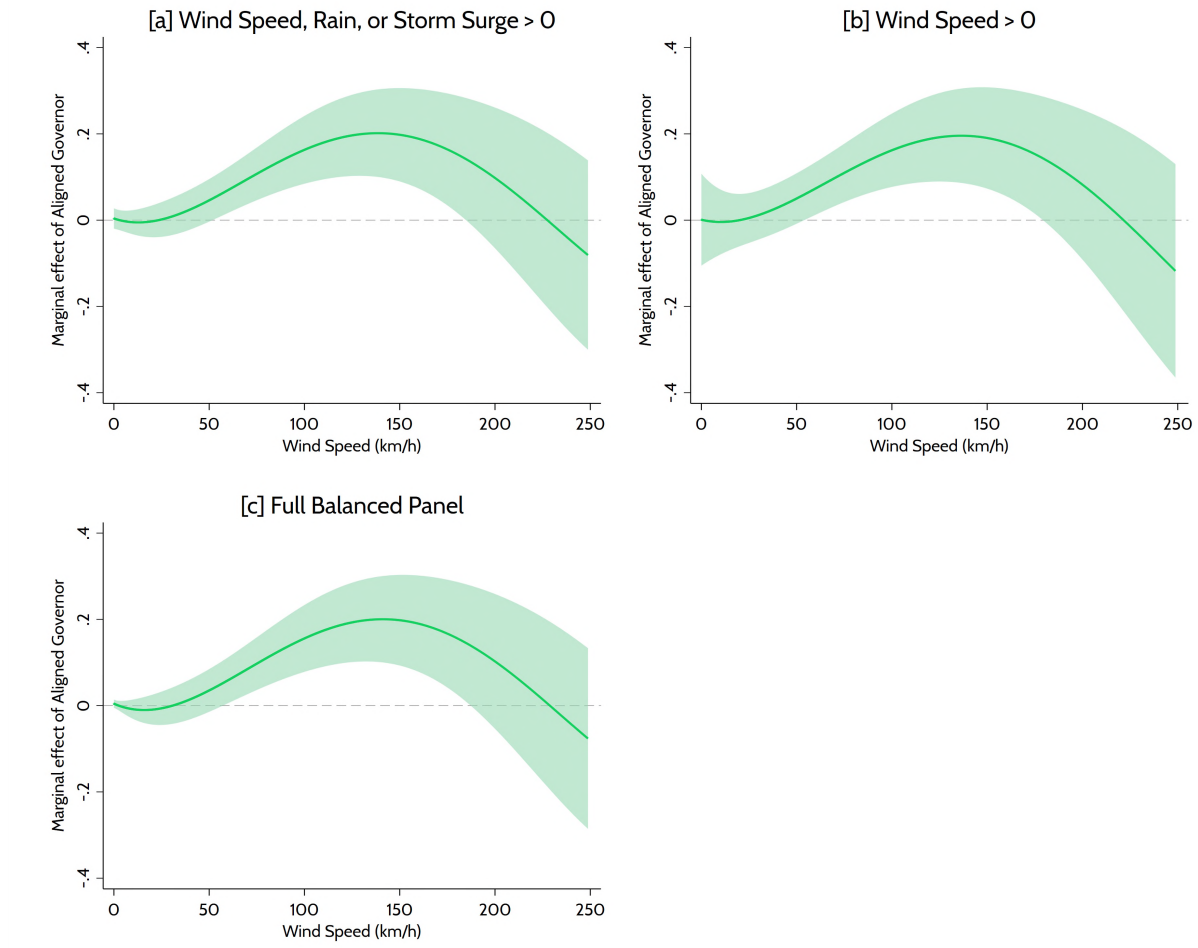


Figure H3: Alternative Sample Definitions

This figure shows the sensitivity of our results to additionally including data from non-coastal states. It 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 estimation specification corresponds exactly with the polynomial specification used in Figure 2 in the paper. Panel [a] includes all county-year observations with either positive *Wind Speed*, *Rainfall*, or *Storm Surge* observations from the contiguous United States. Panel [b] includes only observations with a positive *Wind Speed* observation. Panel [c] uses a full balanced panel, including observations with zero *Wind Speed*, *Rainfall*, and *Storm Surge*.

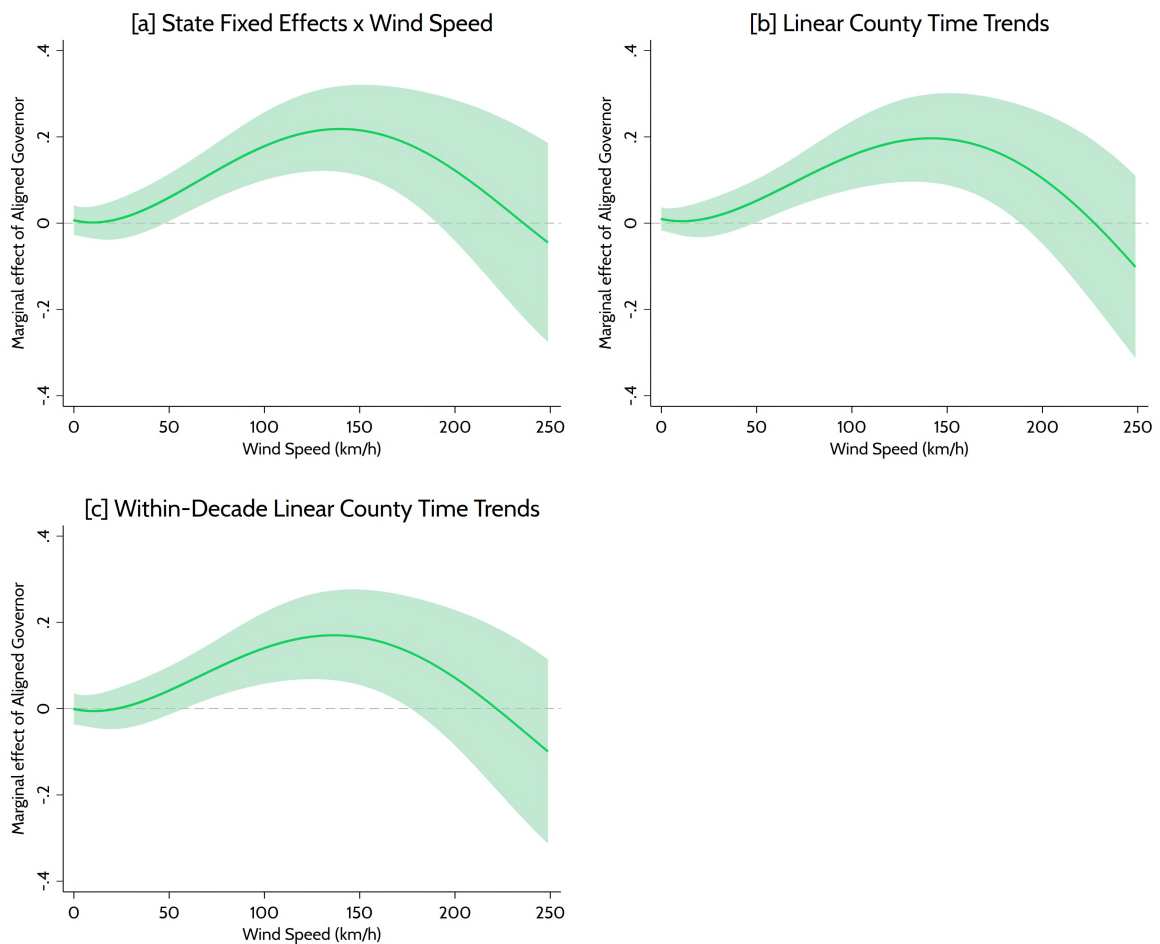


Figure H4: Robustness – State-Specific Wind Speed Controls and Linear Time Trends

This figure shows the sensitivity of our main result to other flexible regression specifications. It 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 to our polynomial estimation. Panel [b] replaces county \times decade fixed effects with county-specific linear time trends. Panel [c] uses within-decade county-specific time trends. Otherwise, these specifications correspond with the polynomial specification used in Figure 2 in the paper.

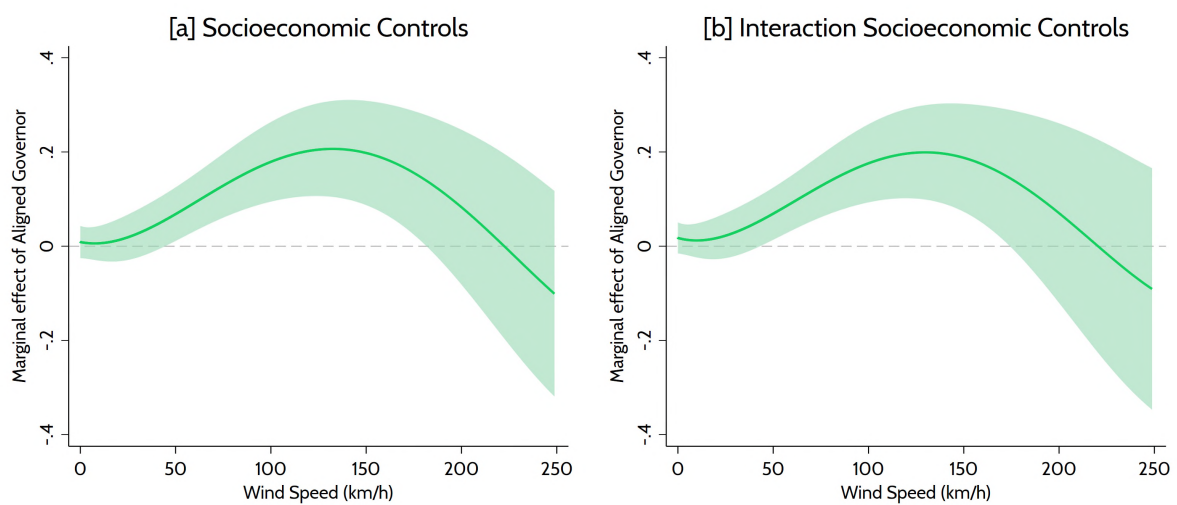


Figure H5: Robustness – Alternative Specifications with Socioeconomic Covariates

This figure shows the robustness of our main result in further flexible 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 1970–2018 due to the limited data availability for county-level income. In Panel [a] the estimation includes *Population (log)*, *Black Population (log)*, *Real Income (log)*, *Per Capita Real Income (log)*, all lagged by one year. Panel [b] includes interactions of all socioeconomic control variables from [a] with the *Wind Speed* polynomial.

Entropy Balancing – Weighted Regressions

To show that the estimates in our quasi-experimental setting are insensitive regarding corrections of potential covariate imbalance, we deploy different approaches of entropy balancing to preprocess our data set in order to obtain a sample balanced on observables. Entropy balancing “calibrates unit weights so that the reweighted treatment and control group satisfy a potentially large set of prespecified balance conditions that incorporate information about known sample moments” (Hainmueller, 2012). The procedure improves balancing of the covariates and their moments specified to achieve null-correlation between the treatment and the observable covariates. The algorithm directly yields balancing scalar weights for each observation, which fulfill the specified balancing constraints but that stay as close as possible to unit weights; these weights can be used to run regressions on a balanced sample (Hainmueller, 2012; Tübbicke, 2020). The method thereby improves upon propensity score matching, which often requires researchers to perform manual iterative procedures to achieve covariate balance (for econometric details, see Hainmueller (2012) and Tübbicke (2020) and the corresponding command manuals provided by the authors).

Entropy balancing has been developed for binary treatments and there exists a novel extension for continuous treatments by Tübbicke (2020), which we also apply. However, it is important to note that matching procedures require the definition of a single treatment variable for which the balancing weights are calculated. In our study, we have a complex non-binary “treatment”, consisting of the interactions of *Aligned Governor* with the wind speed polynomial ($\sum_{b=1}^4 WindSpeed_{i,t}^b \times AlignedGovernor_{s,t}$) in a panel setting. Performing any matching technique to balance the sample on observables requires an arbitrary decision about the variable to perform the balancing for. As, to the best of our knowledge, there exists no standard procedure that is tailored to our approach, we show results for different alternatives of entropy balancing and applying the resulting weights to run a weighted version of our baseline regression. All weighted regressions yield results that are very similar to our baseline.

Since the hurricane-component of our interacted treatment is demonstrably random (cf. Table G9), we focus the efforts of balancing the sample on the alignment indicator. Using the proposed generalization for entropy balancing with continuous variables by Tübbicke (2020), we apply the algorithm to the number of years a state has been aligned. The resulting sample weights thereby ensure covariate balance between states that are differently often aligned. This approach also complies with the fact that entities should not be matched to themselves in different years when performing matching procedures in a panel setting. Despite the obvious methodological caveats in our setting, we also present results using the standard entropy balancing approach proposed by Hainmueller (2012), where we use *Aligned Governor* as a simple binary treatment for the balancing procedure.

In both approaches, we perform the balancing procedures for both the set of socioeconomic controls and our full set of controls (socioeconomic and hurricane-related covariates) to obtain the balancing weights that we feed into our regression. We use the Stata implementations *ebalance* (Hainmueller, 2012) and *EBCT* (Tübbicke, 2020).

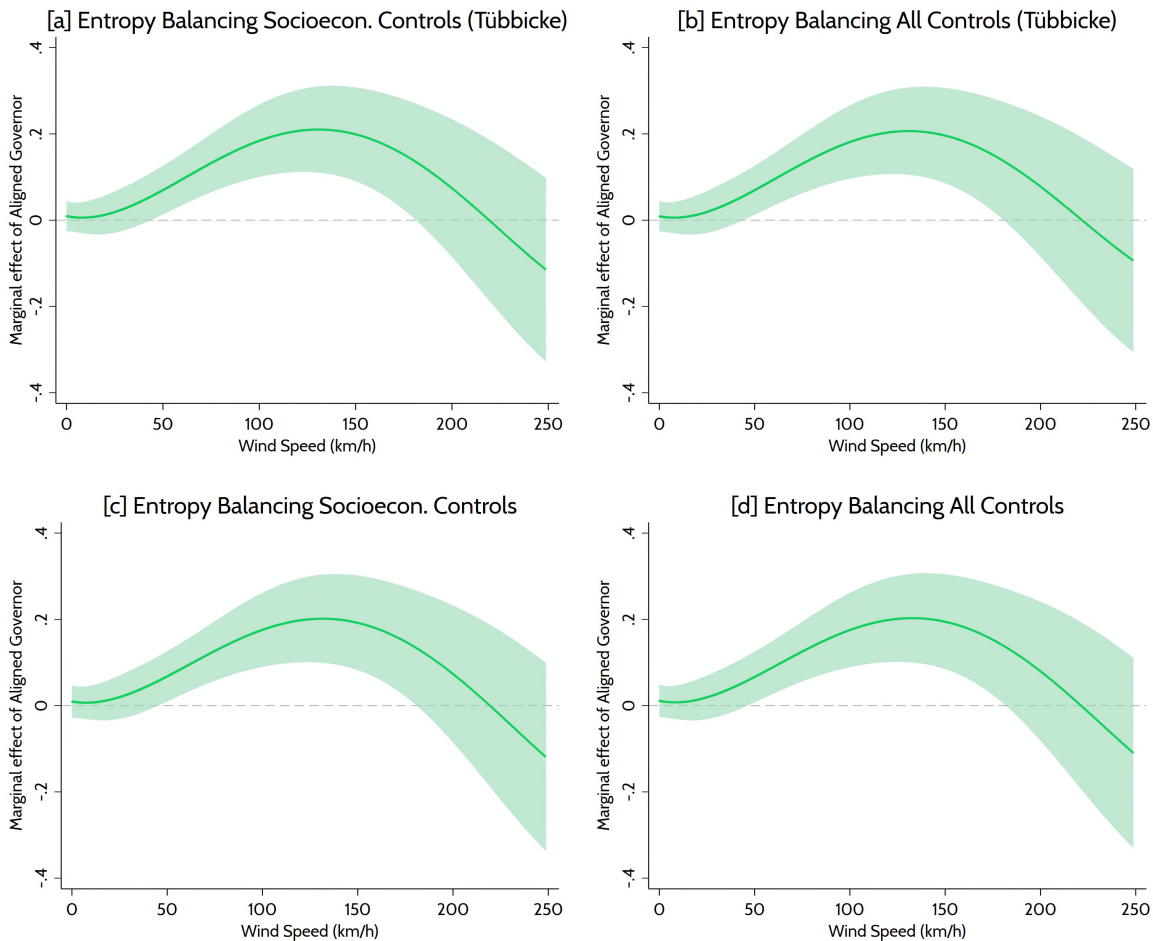
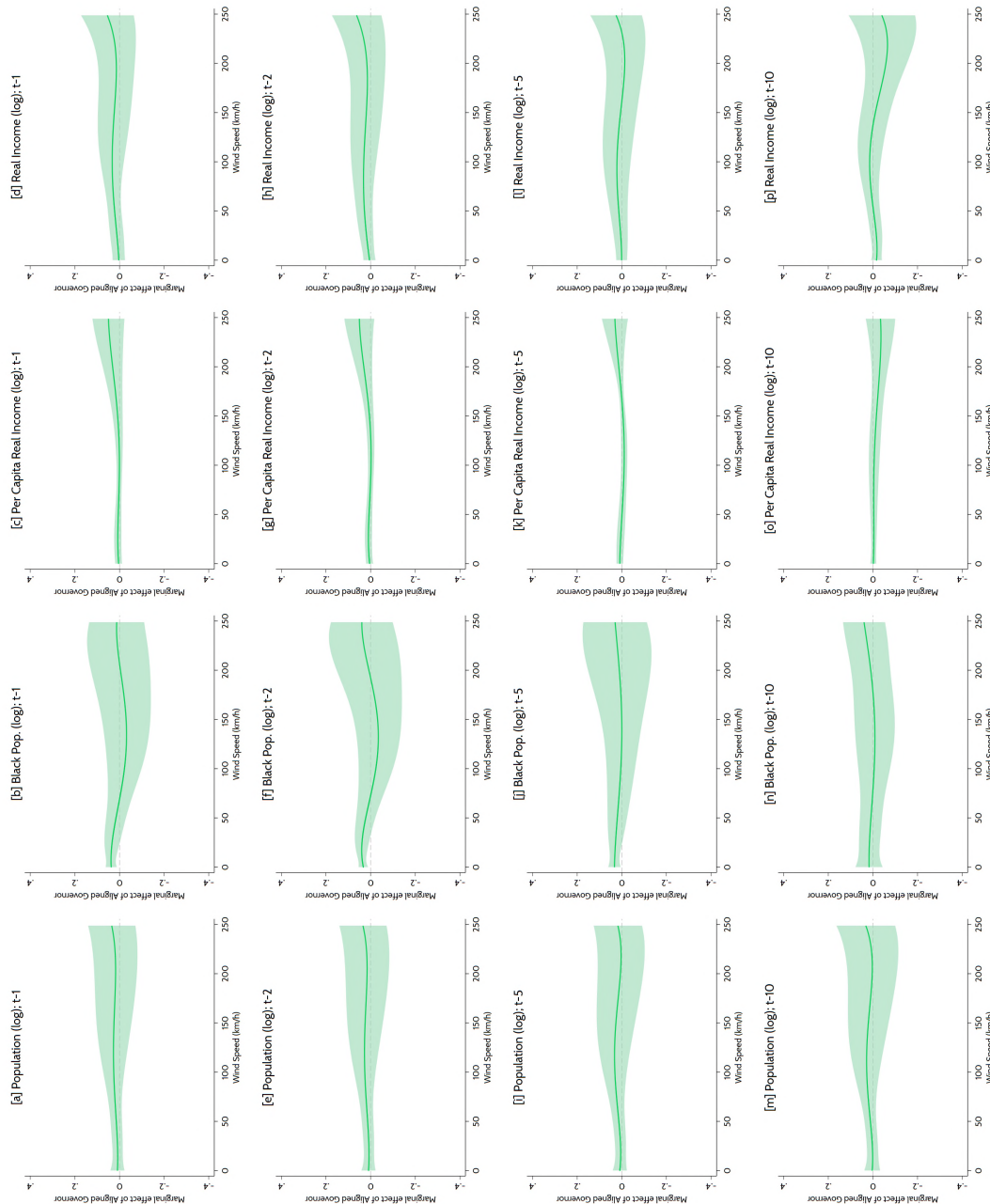


Figure H6: Sensitivity – Entropy Balancing

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 only deviation from the polynomial specification displayed in Figure 2 in the paper is that observations are weighted to obtain a sample that is balanced on different sets of covariates. The weights are obtained from different procedures of entropy balancing. Panel [a] ensures covariate balance using the set of lagged socioeconomic control variables (natural logs of *Population*, *Black Population*, *Real Income*, and *Per Capita Real Income*), considering the total number of years that *Aligned Governor* takes the value 1 in a state as the treatment for which balancing weights are calculated. Panel [b] ensures covariate balance using the full set of control variables, considering the total number of years that *Aligned Governor* takes the value 1 in a state as the treatment for which balancing weights are calculated. Panel [c] ensures covariate balance using the set of socioeconomic control variables, considering *Aligned Governor* as the treatment for which balancing weights are calculated. Panel [d] ensures covariate balance using the set of socioeconomic control variables, considering *Aligned Governor* as the treatment for which balancing weights are calculated.

Figure H7: Exogeneity – Covariates

This figure shows the absence of systematic correlation between pre-hurricane socioeconomic covariates and our main variables of interest (*Aligned Governor* interacted with *Wind Speed*). Each panel displays marginal effects from a separate regression of the dependent variable indicated in the panel title on *Aligned Governor* interacted with the *Wind Speed* polynomial and conditional on the same covariates as in our main regression in Figure 2. The shaded areas represent 95% confidence intervals applying two-way clustered standard errors. All dependent variables are defined in natural logarithms. The panels in the first line use the first pre-hurricane lag of the respective dependent variable, the second line the second lag, the third line the fifth lag, and the fourth line the tenth lag. Joint *F*-tests for the variables of interests are not significant at the 95% confidence level in all but one regression (Panel [p]).



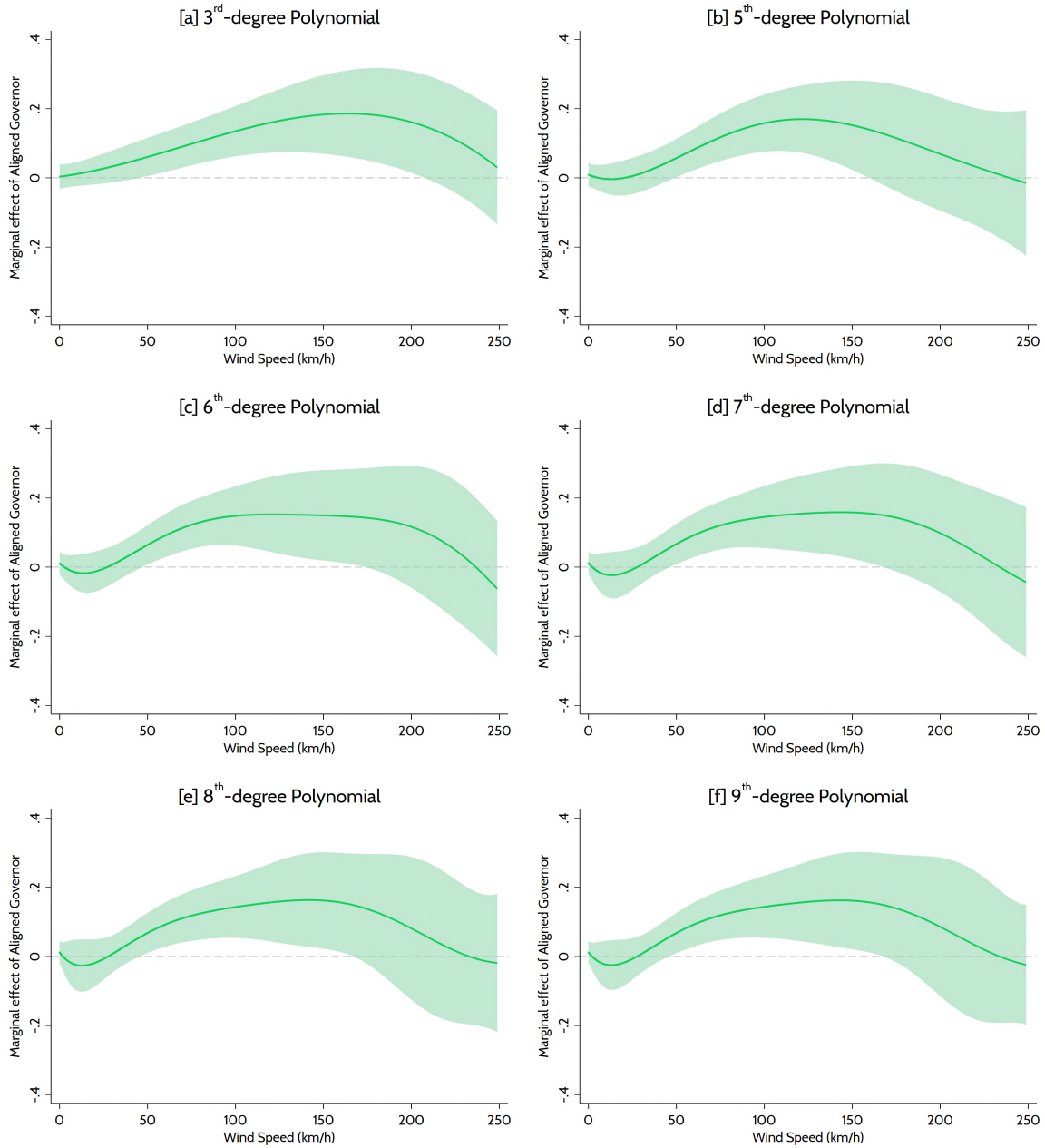


Figure H8: Robustness – Higher *Wind Speed* Polynomials

This figure shows the sensitivity of our main result to applying different polynomial degrees of *Wind Speed*. It 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.

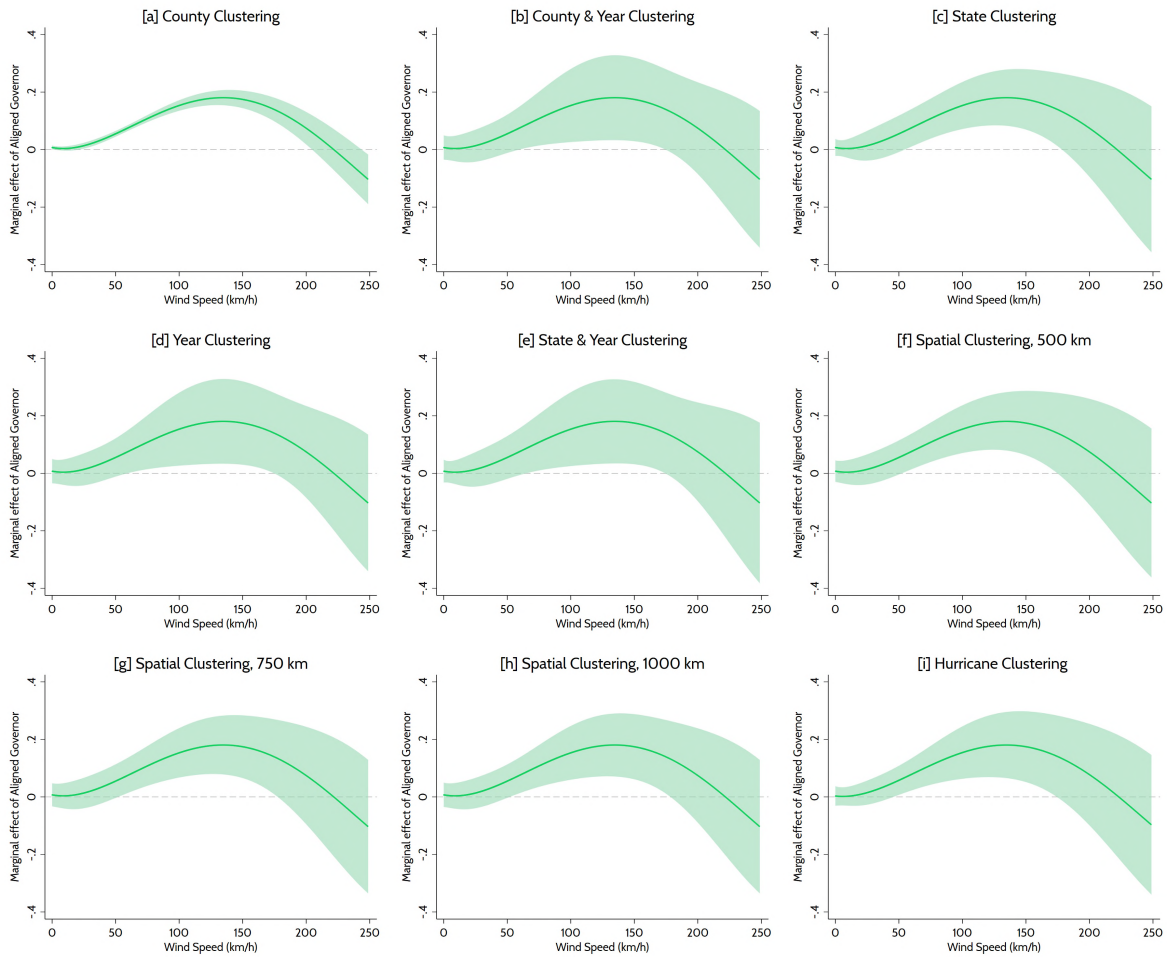


Figure H9: Robustness – Alternative Clustering Choices

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The estimation specification corresponds exactly with the polynomial specification used in Figure 2 in the paper. The light green shaded area represents the 95% confidence interval applying the alternative clustering levels as indicated in the panel titles. Panels [f]–[h] apply a HAC spatio-temporal clustering for different radii (500/750/1000 km) and a 10 year cut-off. The number of clusters in the different dimensions is: 1,136 at the county level, 18 at the state level, 54 at the year level, and 303 at the hurricane level. The sample covers county-year observations from 1965–2018.

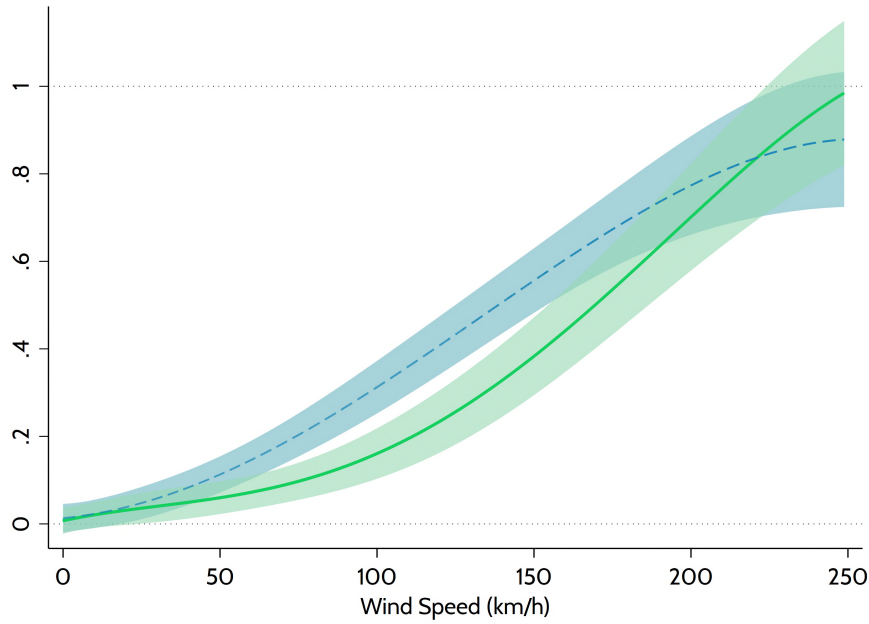


Figure H10: **Predicted Probabilities for a Disaster Declaration**

The figure shows the predicted probability for a disaster declaration in an average county depending on its alignment status, derived from our polynomial estimation. The dashed blue line represents the estimated average declaration probability if a county is aligned, the green solid line plots the probability for unaligned counties respectively. The shaded areas show 95% confidence intervals applying two-way clustered standard errors on the state \times year and county level.

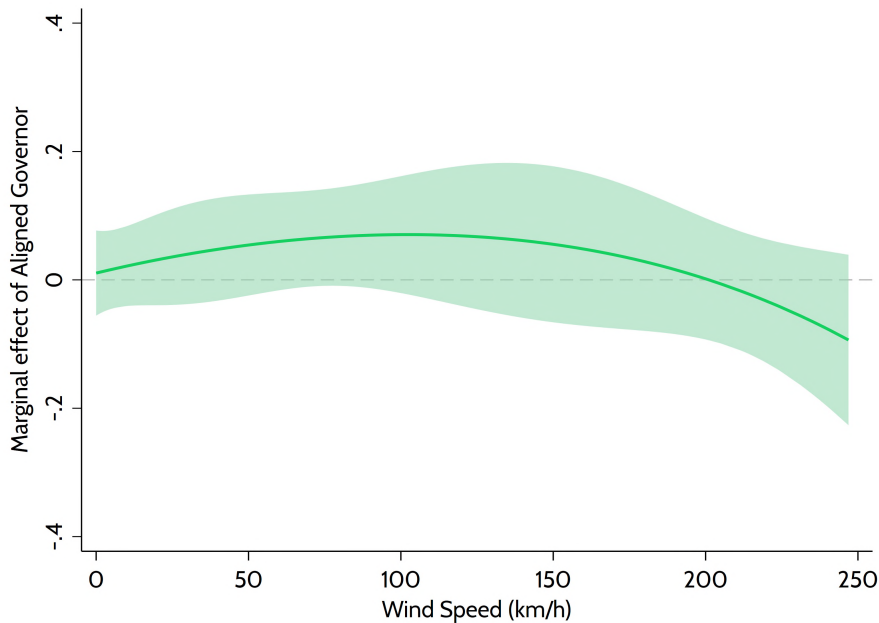


Figure H11: **Extensive Margin**

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 and year level. The data for this estimation are aggregated at the state level. I.e., the dependent variable takes the value 1 if there was a declaration in any county of a respective state and *Wind Speed* measures the strongest wind intensity in the state-year. The specification is otherwise identical with the polynomial estimation displayed in Figure 2 in the paper. The sample covers state-year observations from 1965–2018.

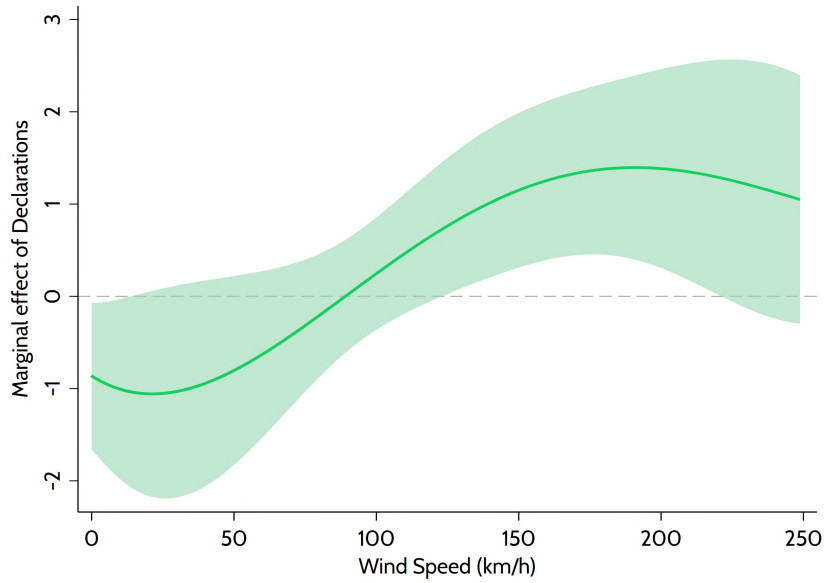


Figure H12: **Declarations and Election Outcomes**

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.

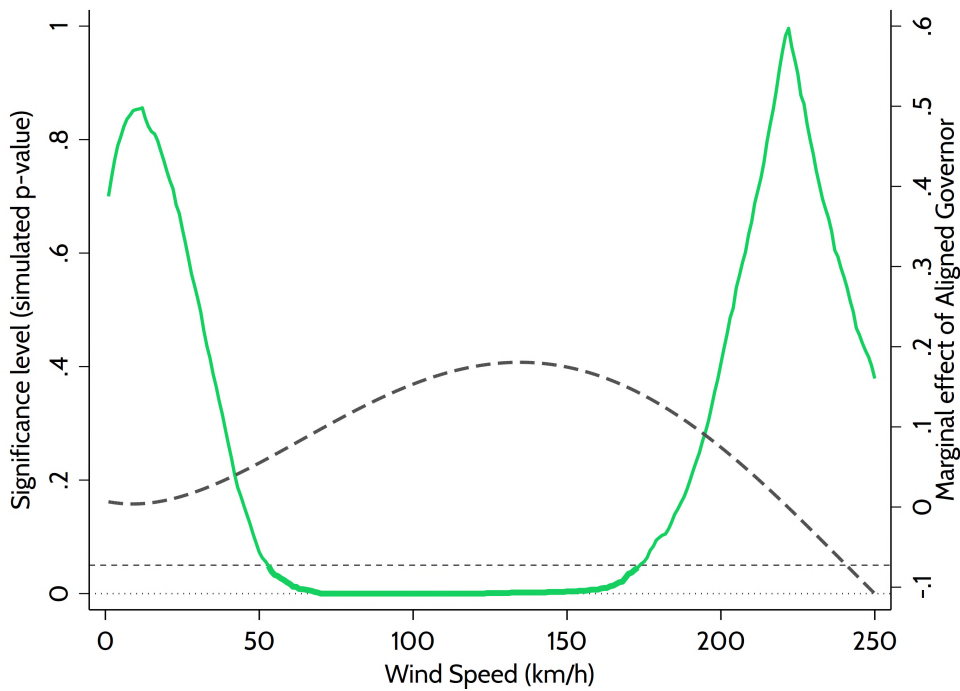


Figure H13: **Randomization Inference: Simulated P-Value**

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 in Figure 3. The gray dashed line represents the coefficient size using the true data.

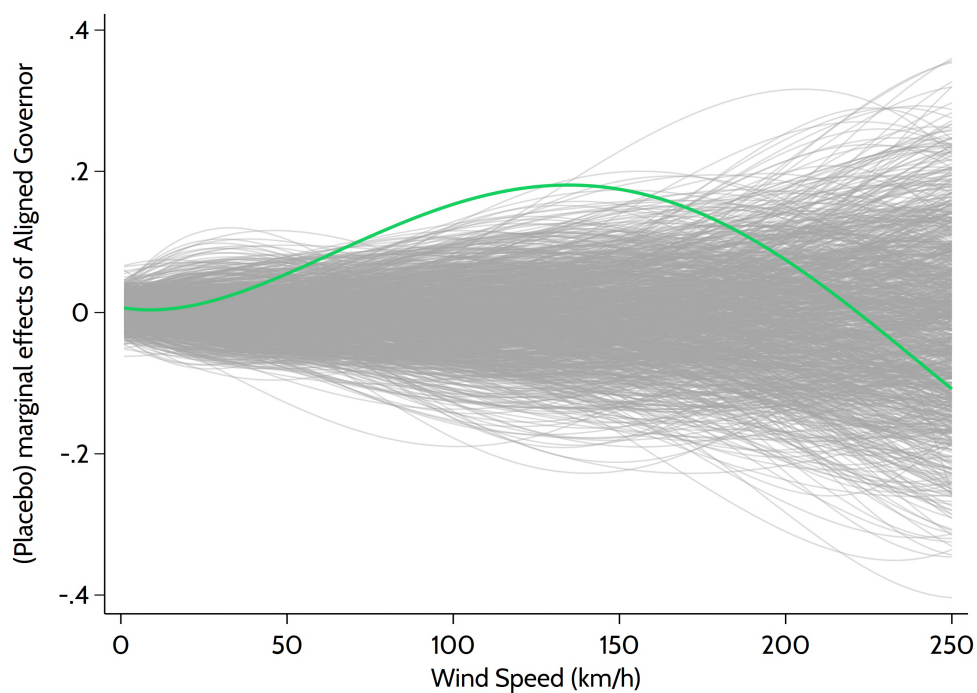


Figure H14: **Randomization Inference: Years**

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 the full pattern of governor alignment status between years; i.e., we assign the alignment status of all states from a specific year to a different year.

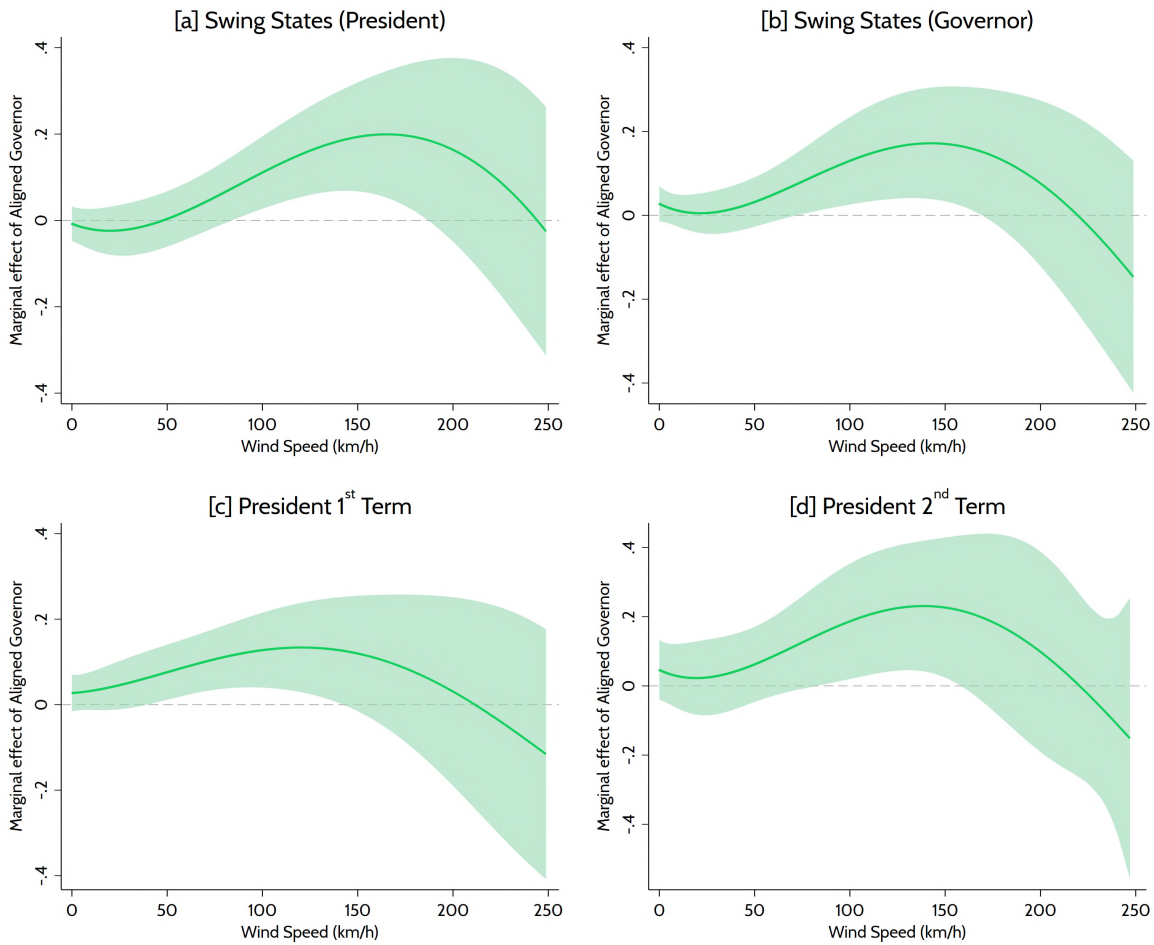


Figure H15: Swing States and Different Terms of the Presidents

This figure shows the sensitivity of our main result in different subsamples. It 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 estimation specification corresponds exactly with the polynomial specification used in Figure 2 in the paper. 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.

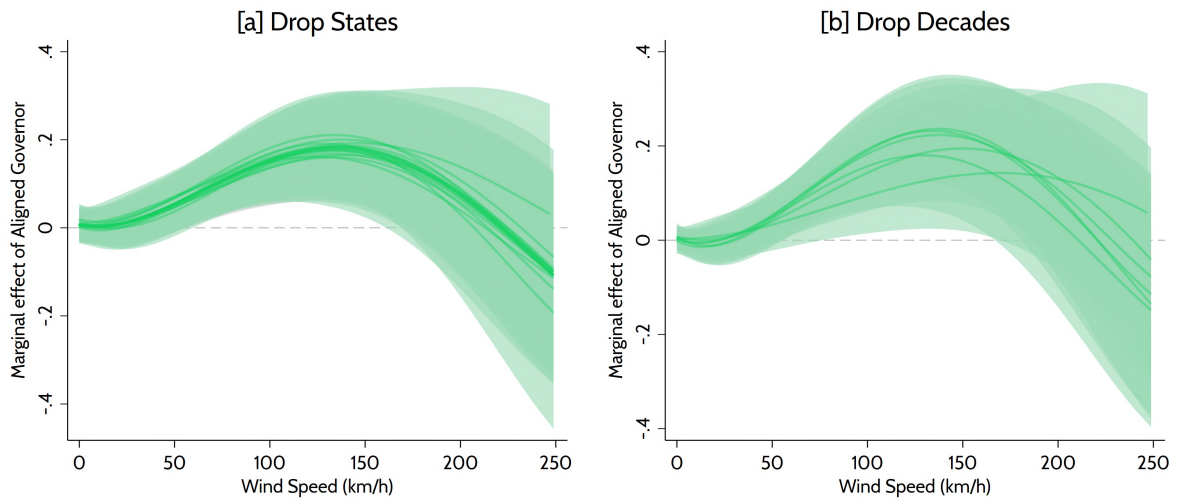


Figure H16: **Robustness – Omitting States and Decades**

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 of the 18 states [a] or six decades [b] covered by our baseline sample. The estimation specification corresponds exactly with the polynomial specification used in Figure 2 in the paper. 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.

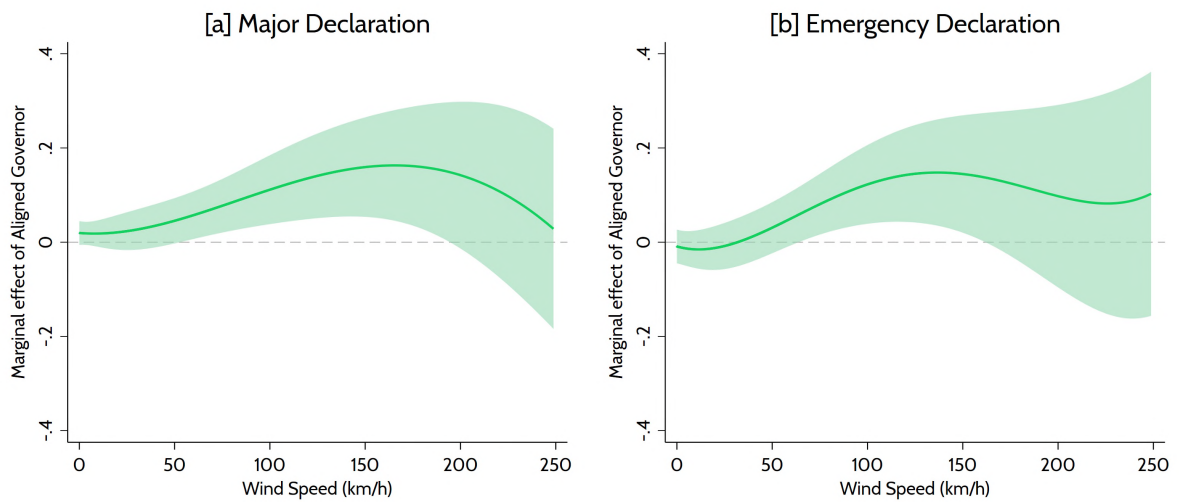


Figure H17: **Major Disaster Declarations and Emergency Declarations**

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*. Otherwise, the estimation specification corresponds exactly with the polynomial specification used in Figure 2 in the paper.

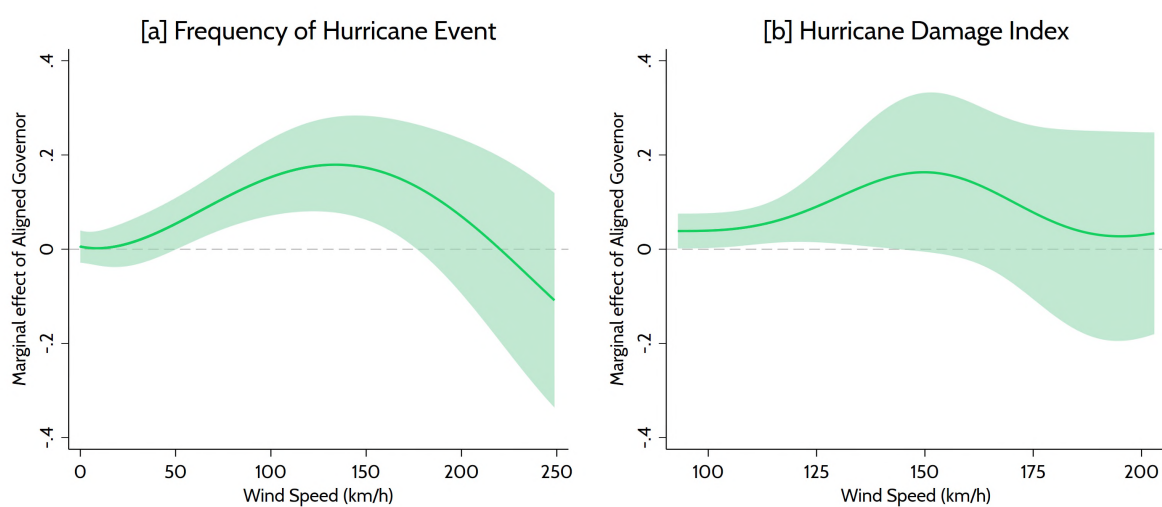


Figure H18: **Robustness – Alternative Damage Proxies**

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 Hurricane *Wind Speed* and *Rainfall* occurrence respectively. Panel [b] applies the wind speed damage index with the assumptions proposed by Emanuel (2011) instead of using our *Wind Speed* polynomial as the damage proxy. Due to the functional form assumptions of the index, its damage approximation assumes a lower-bound threshold of 93 km/h *Wind Speed* (cf. Appendix E).

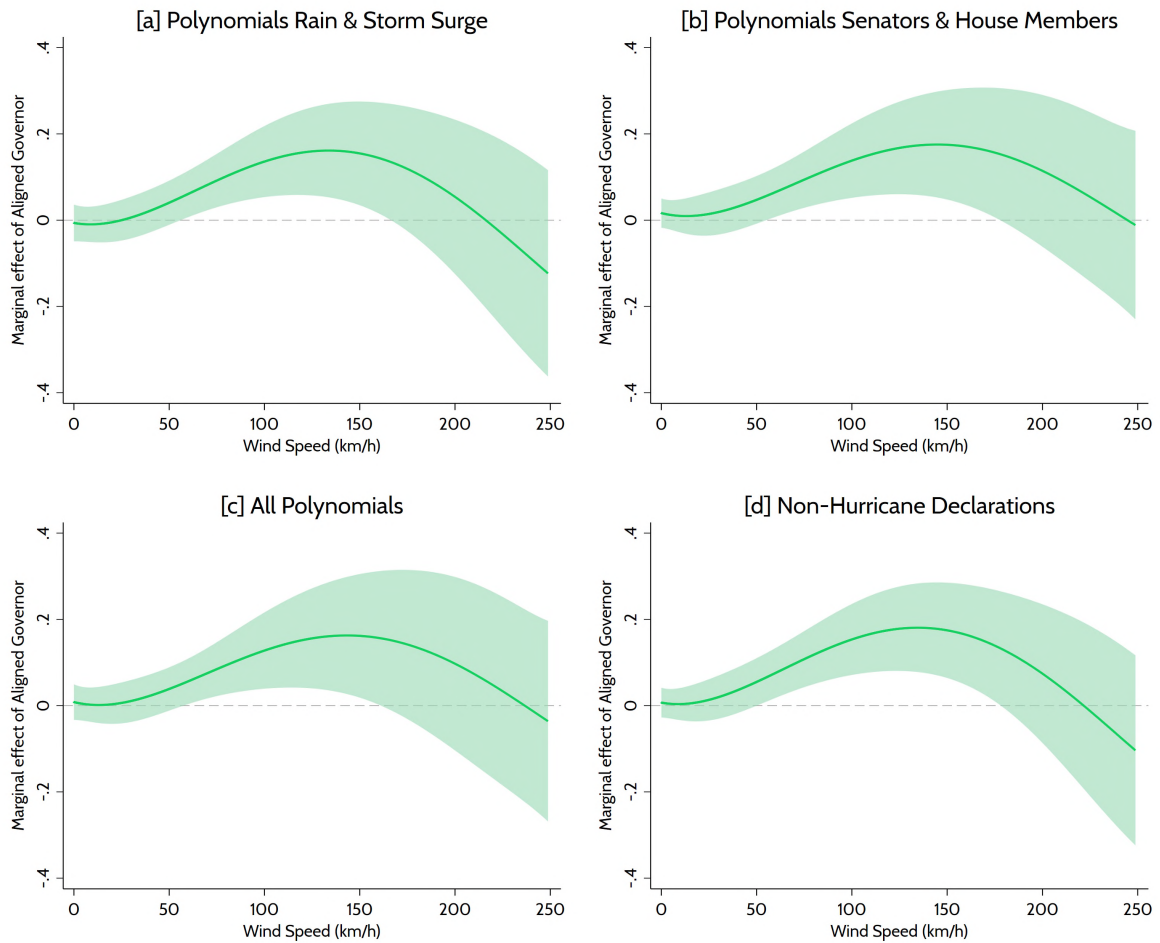


Figure H19: Robustness – Polynomial Controls and Other Declarations

This figure shows the robustness of our main result to further flexible specifications. It 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 non-hurricane-related disaster declarations per county and year.

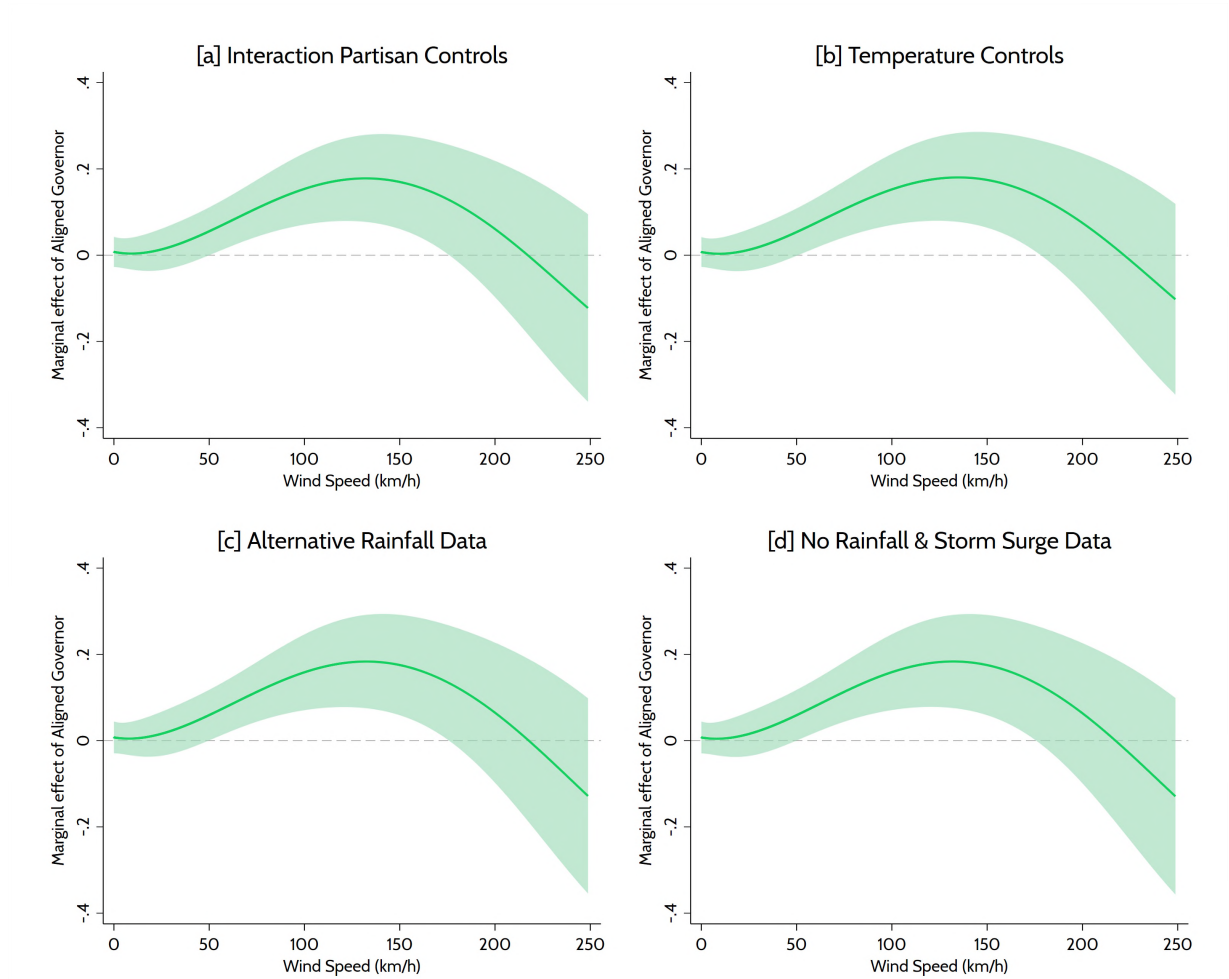


Figure H20: Robustness – Alternative Specifications

This figure shows the robustness of our main result to further flexible 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 the interaction of a party affiliation indicator for Democrats with the *Wind Speed* polynomial. Panel [b] includes additional temperature controls (*Mean Annual Temperature*) from the Prism data base. Panel [c] uses alternative rainfall data (*Mean Annual Rainfall*) from the Prism data base. Panel [d] omits the *Rainfall*- and *Storm Surge*-controls.

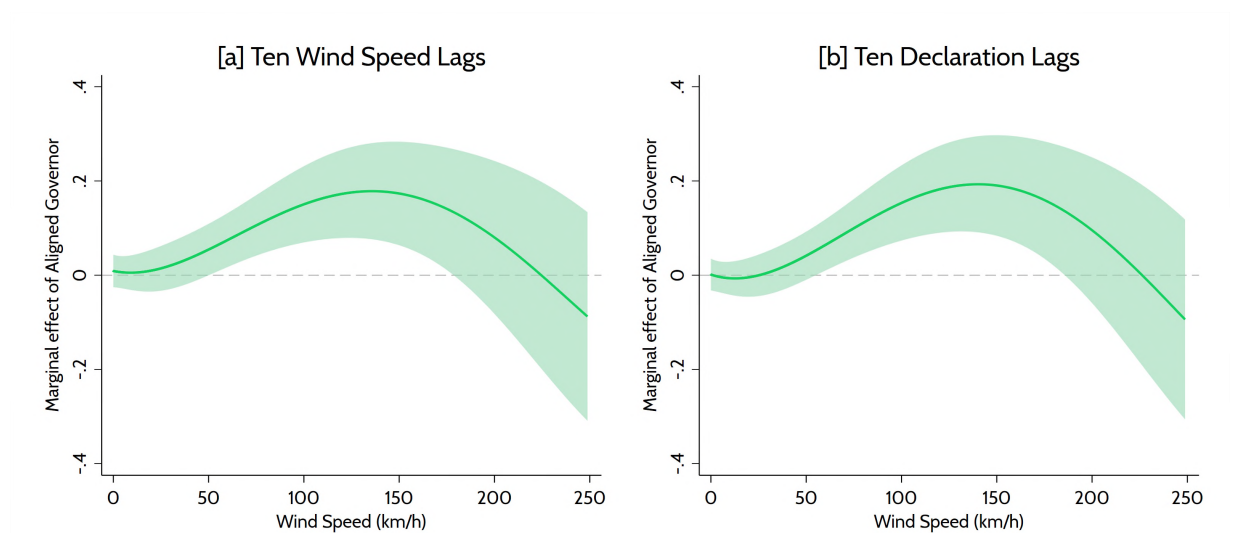


Figure H21: **Robustness – Lags**

This figure shows the robustness of our main result to controlling for long, persistent past hurricane shocks and 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] adds the first ten lags of *Wind Speed* and Panel [b] the first ten lags of *Declaration*.

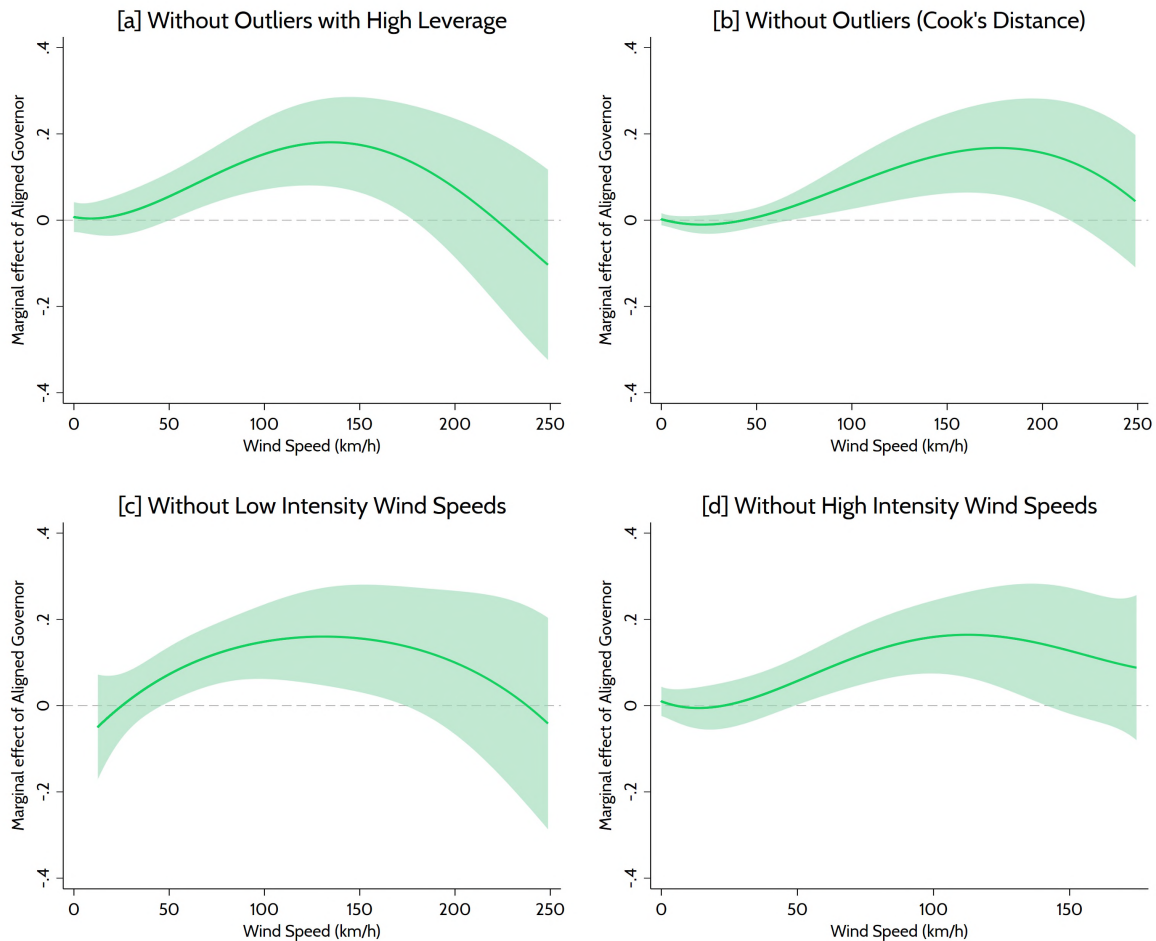


Figure H22: **Robustness – Excluding Outliers**

This figure shows the sensitivity of our results to excluding extreme observations and outliers. It 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 (192 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 $4/n$.

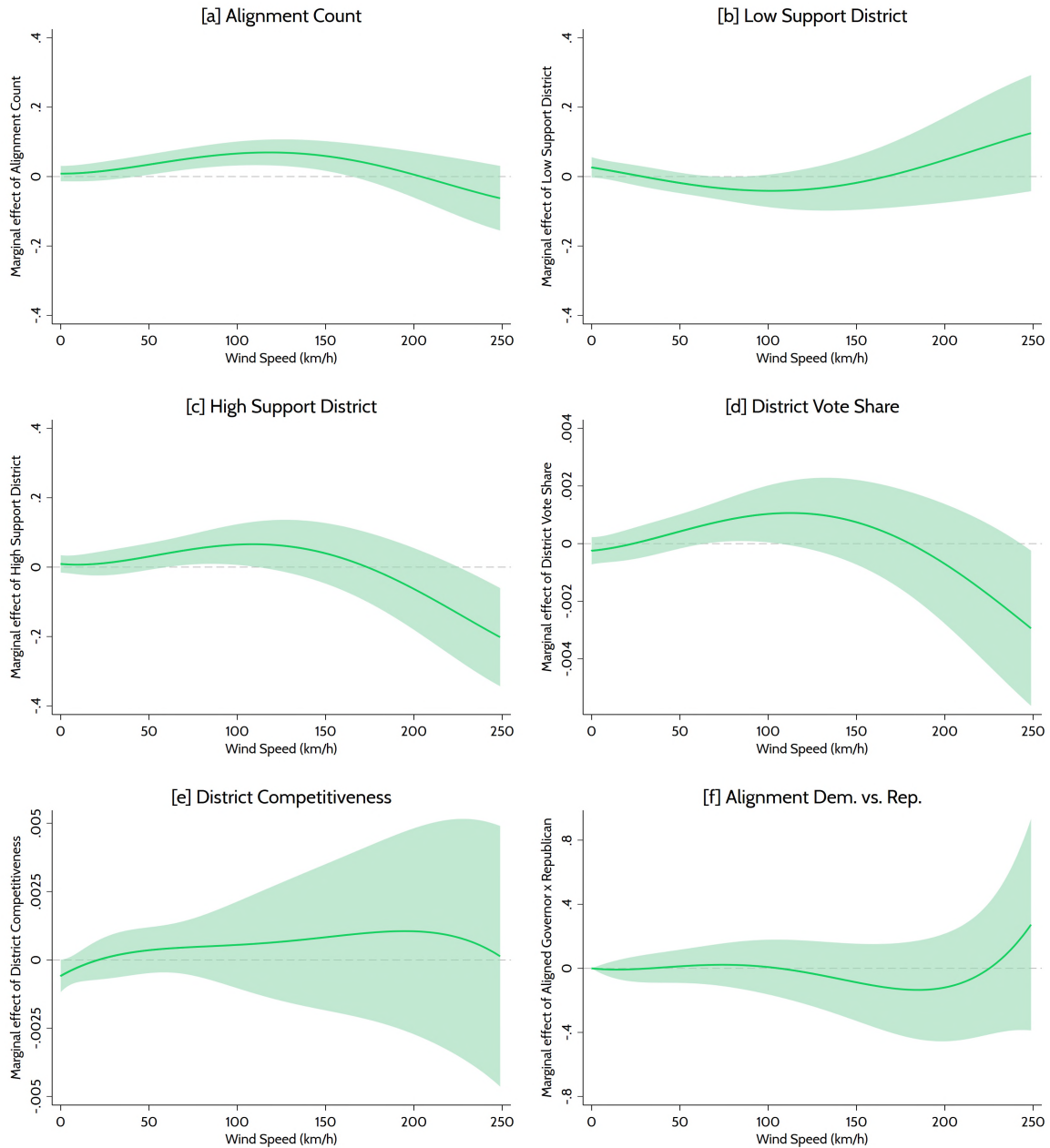


Figure H23: Additional Specifications and Further Political Heterogeneities

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 [c] *Low-Support District* is an indicator that takes the value 1 if the candidate from the party of the incumbent president received less than 40% of the two-party vote share in the previous congressional election; *High-Support Districts* in Panel [c] are those where the president’s party received more than 60%. In Panel [d], *District Vote Share* is the two-party vote share for the district candidate of the incumbent president’s party in the previous congressional election. District competitiveness in Panel [e] measures closeness in a congressional race on a scale from 50 (the two strongest candidates received the equal number of votes) to 0 (one candidate received all the votes). Panel [f] shows differences of *Aligned Governor* between Democrats and Republicans from triple interactions, using an indicator for Republican presidents.

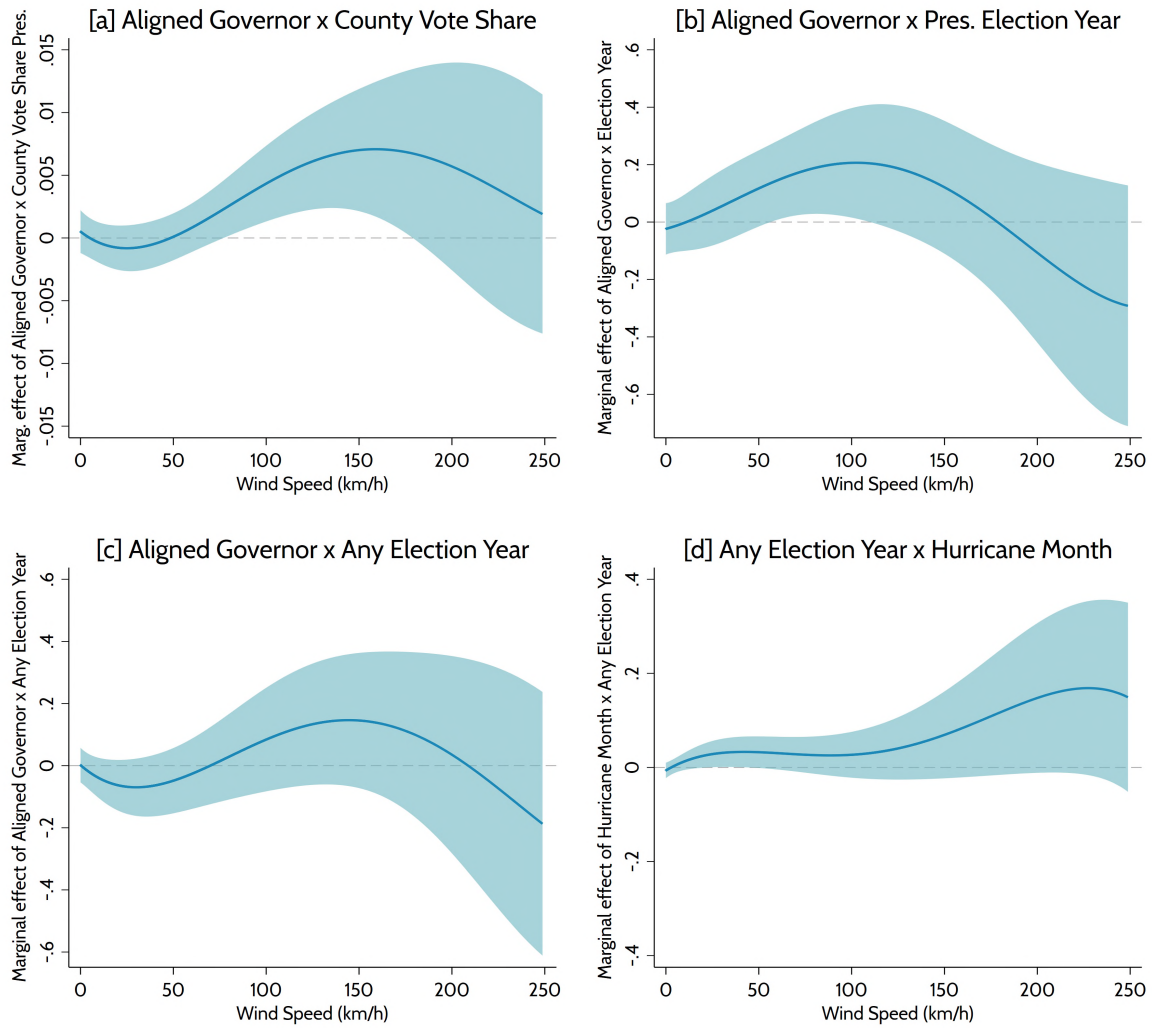


Figure H24: **Political Relief Cycles – Marginal Effects from Triple Interactions**

The figure displays marginal effects for the variable specified on the respective vertical axis from four 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 in Figure 7, 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.

I Relief Amounts and Political Share of Disaster Relief

This appendix explains our procedure to estimate the political share of the annual relief amounts associated with hurricane-related disaster declarations. For this calculation, we use the storm and declaration data from our main analysis and data on FEMA relief amounts. FEMA (2019) provides these data on the county-level only for the post-1998 period for data on public assistance and post-2004 for individual assistance, which reduces the sample for this sub-analysis to less than 20 years.

1. We aggregate all public assistance and individual assistance payments for hurricane-related disaster declarations at the county-year level. Our calculations assume that relief payments are, *ceteris paribus*, proportional to county populations. We use real 2015-US dollars to allow for comparability over time. To obtain an estimate for the monetary amount of FEMA declarations associated with a certain level of storm damage, we regress the reported payments on the well-established wind speed damage index by Emanuel (2011). Consequently, we obtain a nonlinear per capita estimate of FEMA payments for each potential level of hurricane intensity. This accounts for the fact that low storm intensities entail negligible relief amounts in case of a declaration, while extreme storm events require disproportionately high relief payments.

2a. Due to the extreme differences in payments for storms of different strengths, it is crucial to factor in the skewed distribution of wind speeds (cf. Appendix Figure E2). Low wind speed observations occur much more frequently than the extreme ones, which cause the highest payments. To account for this, we derive, in a second step, the annual average distribution of wind speeds. We calculate a nonlinear density estimate for the occurrence of wind speeds in our sample.

2b. Another important property to factor in the calculation is that not every storm event involves a disaster declaration, which then leads to FEMA payments to the respective counties. More extreme storms relate to a higher probability of observing a disaster declaration. Therefore, we use our polynomial prediction for the overall probability of a disaster declaration at every level of wind speed (cf. Appendix Figure H2). The most extreme storms entail a declaration in more than 80% of the cases while, e.g., only about 20% of the wind speed observations at 90 km/h imply a declaration.

2c. Finally, we multiply both the predicted probability to receive a declaration for a certain wind speed (from step 2b) and the per capita amounts associated with a declaration for a specific storm intensity (from step 1) with the estimated annual average wind speed density (from 2a). To obtain an estimate of total relief amounts we additionally need to multiply this prediction curve with the affected population. This accounts for the fact that, e.g., coastal population centers might experience different wind speeds than less populated counties, on average. We regress county population on our *Wind Speed* polynomial to obtain this prediction.

We obtain a prediction function that shows the annual estimate of per capita FEMA transfers to the counties for all observations with a specific wind speed. One can see that the highest share of annual payments is related to wind speeds between 150 and 200 km/h. Expected cumulated payments decrease

for wind observations above 200 km/h because these events are rare. Calculating the integral below this curve (the green area in Figure I1) delivers an estimate of the average total annual amount of hurricane-related federal relief per year. This amounts to roughly USD 4.5 billion. To sum up, step 2 provides an estimate of the amounts that FEMA spends in an average storm season.

3. Ultimately, we are interested in estimating the “political share” of relief payments. Our main result (see Figure 2 in the paper) yields the differences in the probability to receive a declaration at each specific wind speed that stems from political alignment. Multiplying these estimates with the estimated per capita relief amounts for a declaration (step 1), the annual storm distribution (step 2a), and population, we receive a curve that shows the strength of the political effect in monetary terms. The integral below this curve (blue area in Figure I1) yields the estimated annual political amount of hurricane-related FEMA expenditure. Dividing this amount by the estimated total annual amount, we obtain an estimate for the political share of the hurricane-related FEMA payments.⁵³ Approximately 10% of the FEMA payments (~USD 450 million) are attributable to political alignment.

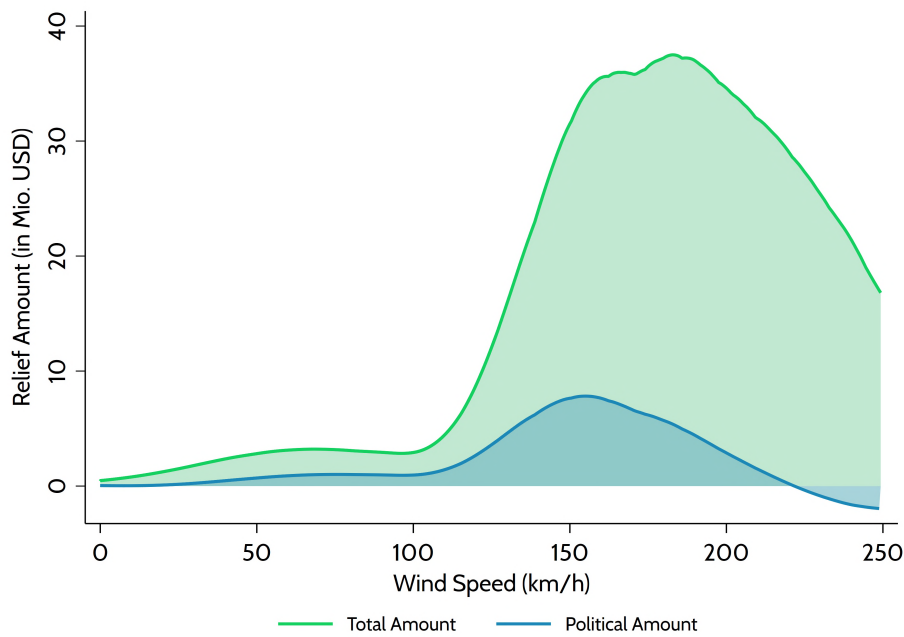


Figure I1: **Total Relief Amounts and Share Associated with Political Bias**

The figure shows the estimated annual average payments for all wind intensities. The area below the green curve represents estimated total annual hurricane relief payments. The integral under the blue curve is the estimated fraction of relief that is explained by the political alignment bias.

⁵³Accordingly, the equation to calculate the political share of relief is as follows:

$$\text{Political Relief Share} = \frac{\int_0^{+\infty} \Delta \mathbb{P}(\overline{\text{Declaration}}|s) \times \phi(s) \times \hat{\kappa}(s) \times \overline{\text{Amount}}(s) ds}{\int_0^{+\infty} \mathbb{P}(\overline{\text{Declaration}}|s) \times \phi(s) \times \hat{\kappa}(s) \times \overline{\text{Amount}}(s) ds},$$

where $\Delta \mathbb{P}(\overline{\text{Declaration}}|s)$ represents our main result (the difference in the probability to observe a disaster declaration due to political alignment), $\phi(s)$ is the annual distribution function of wind speeds s , $\hat{\kappa}$ is the estimated average county population affected by wind speed s , and $\overline{\text{Amount}}(s)$ represents the average per capita transfers through FEMA’s public assistance and individual assistance programs associated with hurricane intensity s in case of a declaration.

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