# Disastrous Discretion

## *Political Bias in Relief Allocation Varies Substantially With Disaster Severity*

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**Abstract**: Allocation decisions are vulnerable to political influence, but it is unclear in which situations politicians use their discretionary power in a partisan manner. We analyze the allocation of presidential disaster declarations in the United States, exploiting the spatiotemporal randomness of all hurricane strikes from 1965-2018 along with changes in political alignment. We show that decisions are unbiased when disasters are either very strong or weak. Only after medium-intensity hurricanes do areas governed by presidents' co-partisans receive up to twice as many declarations. This hump-shaped political bias explains 8.3 percent of overall relief spending, totaling about USD 400 million per year.

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

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

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# 1 Introduction

The allocation of funds through discretionary mechanisms is a fundamental and unavoidable function of government. But discretion can open the door to discrimination and favoritism, 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] It is an important but open question in which situations decisions are susceptible to favoritism and partisan decision-making.

We document a substantially heterogeneous political bias in outcomes of executive decision-making. Studying the political reaction to hurricanes, we demonstrate that the degree to which political considerations guide the provision of disaster relief varies systematically with disaster intensity. We make use of random spatiotemporal variation in physical intensities of all hurricanes hitting the United States from 1965–2018. Our focus is on quantifying when and by how much U.S. presidents favor aligned areas, i.e., those governed by their co-partisans, when allocating federal disaster declarations. We find that outcomes are not biased when a disaster is either very strong or very weak. In the case of medium-strength hurricanes, the alignment bias is substantial and exceeds average estimates at least by a factor of four.

We focus on the president's binary choice to issue a disaster declaration in counties affected by hurricane events. Hurricanes are the most destructive natural disasters in the United States (e.g., Deryugina, 2017; Deryugina et al., 2018; Strobl, 2011). 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.[2] A federal disaster declaration is the requirement for relief provision by the Federal Emergency Management Agency (FEMA).[3] Disaster declaration decisions are a unilateral 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.[4] The president does not decide actual relief amounts,

[1] Previous 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., Albouy, 2013; Berry et al., 2010; Curto-Grau et al., 2018; Solé-Ollé & Sorribas-Navarro, 2008). 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 political budget cycles and favoritism in the domains of foreign aid (Bommer et al., 2022; Eichenauer et al., 2020; Faye & Niehaus, 2012), monetary policy (Aidt et al., 2019), and the Bretton Woods institutions (e.g., Dreher et al., 2009; Lang & Presbitero, 2018).

[2] See NOAA (2019), as of January 11, 2021. For socioeconomic effects of hurricanes cf., for instance, Barrage & Bakkensen (2021), Elliott et al. (2015), and Kunze (2021).

[3] Relief payments from FEMA are important in magnitude, averaging about USD 8 billion per year between 2009–2018 (Stein & Van Dam, 2019). Data on the actual relief amounts paid out for hurricane disasters to individual counties are only available for a limited period starting in 1998.

[4] Data on governors' declaration requests were not publicly available at the time of writing. The data that we received via a Freedom of Information Act inquiry from FEMA have stark temporal limitations. For completeness, we report a short summary of the data in the appendix.

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 decision-making process.

Hurricanes exogenously trigger this decision-making process. Given different baseline risks between counties, the timing, location, and severity of hurricane strikes are determined by a stochastic meteorological process, thus being random and unpredictable (e.g., Hsiang, 2010; Strobl, 2011). Consequently, we observe a quasi-experiment in which presidents have to make decisions as to whether a federal disaster declaration is necessary in light of a wide variety of observed disaster intensities. We combine temporal variation in political alignment of governors and presidents with high spatial resolution data on the physical strengths of hurricanes at different locations. Our strategy captures the causal political alignment effect for different storm intensities, using 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 flexible measures of hurricane intensity. Our identifying assumption is that there exists no other factor that systematically explains both the political alignment status and the probability of a county to receive a disaster declaration for a given storm intensity. We show that our results also hold in a close election subsample.

The results from our estimations show a distinct heterogeneous pattern for the alignment bias. The probability of observing a disaster declaration in an area with medium intensity increases by up to 18 percentage points when the governor and the president are from the same party. Alignment almost doubles the declaration likelihood for the same disaster intensity compared to a situation when governor and president are unaligned. This effect is more than four times higher than the results from conventional average estimates that pool all storm intensities. Our nonlinear estimates demonstrate that, for low and extremely high wind speeds, the influence of political alignment is close to zero and insignificant. When hurricanes are weak, disaster declarations are rare; when hurricanes are very strong, disaster declarations are almost universal – irrespective of political alignment. The evidence suggests that the primary mechanism for the pronounced bias at medium storm intensities operates at the intensive margin – i.e., how many counties are included in a declaration – rather than at the extensive margin – i.e., whether a disaster is declared at all. We calculate that the political alignment bias for hurricane-related disasters amounts to approximately USD 400 million on average per year. This corresponds to approximately 8.3% of total annual hurricane relief payments.

Our findings demonstrate that some decision situations are prone to biased outcomes while other are not. This extends the political-economic literature as it adds to the understanding of strategic behavior

of decision-makers, particularly about alignment biases in distributive politics (e.g., Arulampalam et al., 2009; Bracco et al., 2015; Brollo & Nannicini, 2012; Fiva & Halse, 2016).[5] The explanation for the hump-shaped causal pattern that we identify for alignment, which we find most plausible, is that politicians exploit unclear circumstances for strategically biased allocations. These situations entail plausible deniability, which reduces the reputational costs of taking partisan decisions: whether federal relief is necessary is less obvious for medium strength disasters than for very weak and strong levels of destruction where public opinion is unanimous.[6] This explanation aligns with evidence about individual favoritism and discrimination, which shows that biased and discriminatory behavior is most likely when there is ambiguity about the objectively optimal decision (e.g., Bertrand & Duflo, 2017; Garicano et al., 2005; Goncalves & Mello, 2021). Our preferred interpretation is also consistent with results showing that politicians strategically time unpopular executive actions to days when the public is diverted by other events (Djourelova & Durante, 2022; Durante & Zhuravskaya, 2018). However, we cannot rule out other explanations for why political alignment tips the scales in favor of a declaration in medium-intensity situations.

In line with previous analyses of disaster declarations by Gasper (2015), Garrett & Sobel (2003), and Reeves (2011), we show that politicization in the disaster declaration process emerges only after 1988. The emergence of politicization coincides with the passage of the Stafford Act in 1988, which augmented the position of the president to make discretionary decisions about what qualifies for disaster declarations (Lindsay & McCarthy, 2015; Sylves, 2008).

Further heterogeneity analyses are consistent with politicians' tactical-electoral considerations rather than, for instance, mere information advantages in case of alignment explaining our findings. The alignment bias is more pronounced for governors that have been elected with smaller margins and for hurricanes that occur before elections. This resonates with earlier evidence by Cole et al. (2012) and Besley & Burgess (2002) that Indian governments increase calamity relief and public food distribution when political incentives are higher, e.g., in election years and for areas with higher turnout and political competition. These two studies are also seminal in introducing the idea of interacting measures of disaster severity with political factors. Our analysis extends this approach by systematically estimating

[5] The related literature provides theoretical and empirical evidence that politicians can gain in various ways from strategically biased allocations favoring their co-partisans and aligned electoral districts, e.g., to strengthen political ties and to improve their re-election prospects (e.g., Alesina & Tabellini, 2007; Carozzi et al., 2022; Geys & Vermeir, 2014).

[6] The public receives information on disaster assistance from the media, which facilitates political accountability (Snyder & Strömberg, 2010). Governments' relief expenditure is, for instance, higher for areas with better radio reception and newspaper circulation (Besley & Burgess, 2002; Eisensee & Strömberg, 2007; Strömberg, 2004). Several analyses find that voters reward incumbents for generous disaster relief provision (e.g., Bechtel & Hainmueller, 2011; Cole et al., 2012; Gasper & Reeves, 2011; Healy & Malhotra, 2009). Whether the net electoral effects of disasters are positive for politicians is the subject to an evolving debate (Gallagher, 2021).

the heterogeneous pattern of political bias without imposing a linear functional form. Besley & Burgess (2002) argue that politicians' incentives to provide more relief increase in disaster severity, which would explain the initial positive slope of the alignment bias. However, our results demonstrate that political bias in discretionary decision-making can have a distinct non-monotonic pattern. Models that aim to explain political decision-making should incorporate this fact, for instance, when making assumptions about politicians' incentives in different situations. In general, our results yield an important insight into the partisan behavior of executive politicians as they extend our understanding of when they make efficient decisions and in which situations decision-making processes require modification or enhanced monitoring. Our results suggest that relief allocation could be improved by increasing rule-based decision-making, promoting accountability, and depoliticizing disaster relief provision.

## 2 Institutional Background and Data

**Disaster Declarations.** 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 existed since 1950 and works as follows: if a natural disaster overwhelms 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. 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 *Stafford Act* in 1988 augmented the discretionary power of the president to decide which events qualify for a declaration. It states that the president has full discretion to issue a declaration for any "natural catastrophe [...] in any part of the United States, which in the determination of the president causes damage of sufficient severity and magnitude" (Stafford Act, 1988). The president issues a declaration to a specific state and explicitly lists the counties eligible for federal help. While the governor can propose counties for the disaster declaration, "the president [...] may choose to include some but not all of the counties recommended by the governor" (Sylves, 2008, p. 84). Notably, presidents can even declare an emergency without a gubernatorial request when they determine "that an emergency exists for which the primary responsibility for response rests with the United States [...]" (McCarthy, 2014, p. 9).[7] Once a declaration

[7] See Appendix A for further details on the disaster declaration process, different types of declarations, and available spending programs.

is issued, FEMA determines the amount of financial assistance needed and decides which individuals or public entities in the declared area are entitled to relief. However, "the ultimate decision to approve or reject a governor's request for a declaration is made by the president" (Sylves, 2008, p. 94) and their declaration behavior eventually determines whether the allocation of declarations is politically biased.

We observe disaster declarations from the *openFEMA* database (FEMA, 2019), which contains a county listing of all declarations since 1965. Our main dependent variable *Declaration* is an indicator taking the value 1 if a county received at least one hurricane-related disaster declaration in a given year, and 0 otherwise. In our data, 6,553 county-year observations received at least one hurricane-related *Declaration* that could be matched to a hurricane or tropical storm.[8]

**Political Alignment.** 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. 1,136 counties in our main sample were both affected by hurricanes in multiple years and exhibit a different alignment status in at least one treatment year. Analogously, we construct binary variables for congressional politicians' affiliations with the party of the incumbent president (*Aligned Representative* and *Aligned Senators*). Additionally, we exploit data on past election outcomes to test further political channels. For instance, we use different variables measuring electoral support, competitiveness, and margins of victory in previous elections.[9]

**Hurricane Intensity.** Hurricanes are large-scale chaotic weather shocks that hit the United States in a season usually ranging from June to November each year.[10] Even 48 hours in advance, the exact location of a hurricane landfall is impossible to predict (Aguado & Burt, 2015; Rappaport et al., 2009), which is reflected in the erratic behavior of hurricane raw tracks displayed in Panel [a] of Figure 1. Hurricanes typically have three damage sources: wind speed, excessive rainfall, and storm surge. Since wind speed correlates with rainfall and storm surge, we use it as the primary damage proxy in our analysis (Elliott et al., 2019; Kunze, 2021; Strobl, 2011). However, as a robustness test we additionally

[8] See Appendix C for details on the definition of the *Declaration* indicator. Following Reeves (2011), we include both major disaster declarations and emergency declarations in the baseline. We also collected information on disaster declaration denials by the president via a Freedom of Information request (2019-FEFO-00419) to FEMA. Official declaration denials in connection with tropical cyclones account for only 2.5% of the reported requests since 1992. As denials are in any case endogenous to the respective requests and official denials are too sparse for reliable estimation, we refrain from a further analysis but report a brief summary of the data in the appendix for completeness (cf. Table D1).

[9] We document the definitions and sources of all variables mentioned above and further covariates in Appendix C.

[10] See Appendix B for details about hurricane genesis and impacts.

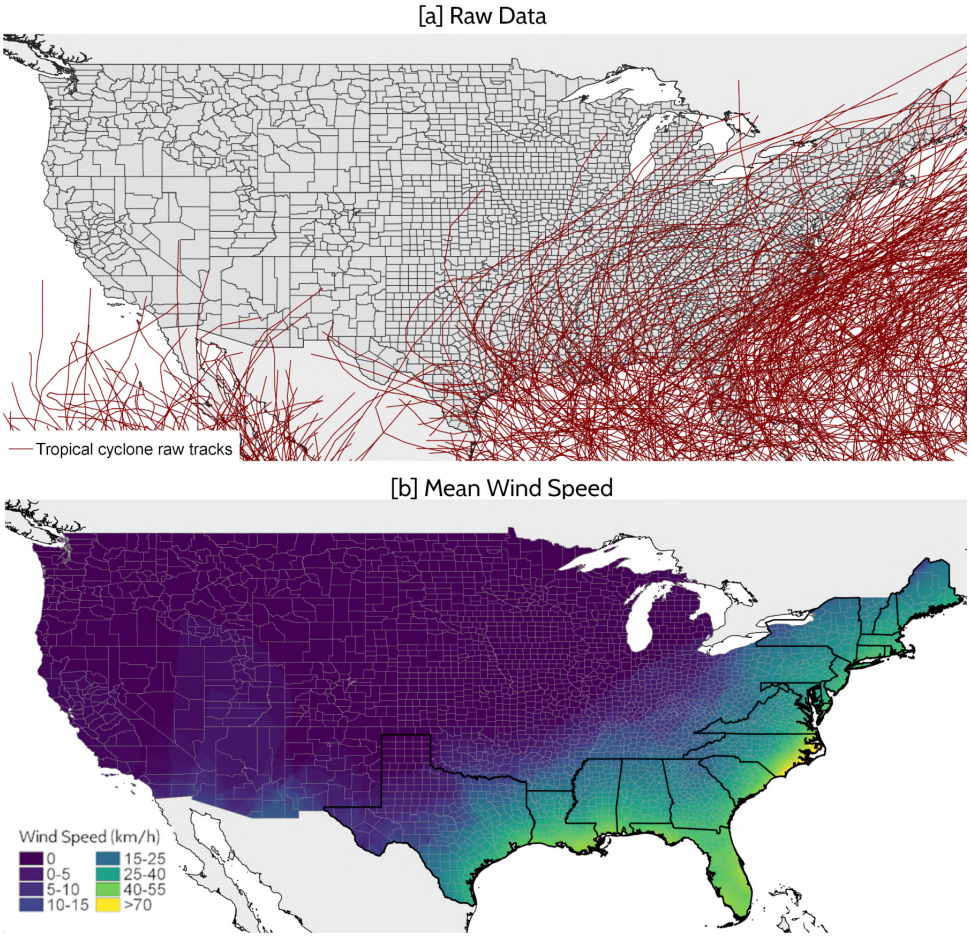


Figure 1: **Hurricane Raw Tracks and Modeled *Wind Speed* Average, 1965–2018**

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 dark 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. Figure B1 shows a *Wind Speed* histogram.

control for new data on hurricane rainfall (Roth, 2018), which is highly localized, and storm surge (Kunze & Strobl, 2020), which only occurs at the coast.

We use meteorological data on wind speed for the years 1965–2018 from the IBTrACS data set (Knapp et al., 2010). It contains data on all hurricanes, tropical storms, and tropical depressions collected from various weather agencies. The raw tracks data include six-hourly observations of the exact position, wind speed, and minimum sea pressure of each storm. To calculate hurricanes' 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 at a resolution of $1 \times 1$ km. 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-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 D1 shows that, for 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%.[11]

In total, our data contains information on 325 tropical cyclones. Panel [b] of Figure 1 displays the average annual wind speed exposure over the 1965–2018 period, as derived from our wind field model. Our baseline sample covers all county-year observations with positive hurricane-related wind, precipitation, or storm surge observations from the states bordering the Atlantic or Gulf of Mexico, as they experience the predominant share of hurricane-related damage. The final panel data set consists of 49,092 county-year observations over the 1965–2018 period.[12] Appendix Table D3 displays descriptive statistics.

# 3 Empirical Strategy

We use the spatio-temporal randomness in hurricane incidence to identify the political bias in presidential disaster declarations. We observe a quasi-experiment in which politicians are randomly selected by a stochastic natural process to make a non-deferrable decision in reaction to a shock unpredictable in timing and location (e.g., Deryugina, 2017; Strobl, 2012). At this point in time, political factors are predetermined; for example, the governor of an area hit by a storm is either aligned or unaligned with the president. Hurricanes generate heterogeneous treatment patterns. They have different strengths and, for each individual storm, damage can range from devastating (for areas hit by the storm's eye) to very light (for those affected by outer bands of a storm system). This implies a variety of decision situations as to whether a declaration is necessary. We rely on the assumption that stronger wind speeds, *ceteris paribus*, cause more damage. Other than that, we are agnostic about the functional forms of hurricane damage and political influence. We estimate equations of the following form:

$$\begin{aligned} Declaration_{i,t} = \alpha + \beta Aligned\ Governor_{s,t} + \sum_{h=1}^{4} \gamma_h Wind\ Speed_{i,t}^{h} \\ + \sum_{h=1}^{4} \left( Wind\ Speed_{i,t}^{h} \times Aligned\ Governor_{s,t} \right) + \mathbf{X}_{i,t}'\mu + \tau_t + \sigma_i \times \zeta_t + \varepsilon_{i,s,t}. \end{aligned} \tag{1}$$

[11] Appendix B describes the wind field model in more detail and explains advantages of applying physical wind speeds over commonly used reported damage data (cf. also Felbermayr & Gröschl, 2014; Gallagher, 2021). Figure B1 displays a histogram for *Wind Speed*.

[12] As robustness tests, we show results of samples restricted to observations with positive *Wind Speed* only, an extended sample of the affected counties from the entire contiguous United States, and a fully balanced panel including county-year observations not affected by hurricanes (see Appendix Figure D2).

*Declaration* is the binary indicator for disaster declarations received by county $i$ in year $t$. To account for nonlinearities in a flexible way, we use a *Wind Speed* polynomial ($\sum_{b=1}^{4} \gamma_b \, Wind\ Speed_{i,t}^{b}$) and interact the entire polynomial with our main variable of interest (*Aligned Governor*). This facilitates estimating the extent of political bias at different wind speeds. We aim for a parsimonious baseline model to not inflate the regression unnecessarily with additional parameters. We use 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 D3).[13] As an alternative to the *Wind Speed* polynomial, we also show a semi-parametric model, defining 25 km/h bins of wind speed $\sum_{j=1}^{10} \gamma_j \, Wind\ Class\ j_{i,t}$ (cf. Deschênes & Greenstone, 2011; Schlenker & Roberts, 2009). Analogously to the polynomial approach, all *Wind Speed* interval dummies are interacted with *Aligned Governor* to estimate a separate marginal effect of alignment for every wind speed interval.

The vector $\boldsymbol{X}_{i,t}$ represents further explanatory variables; in the baseline it comprises the alignment statuses of the House representatives and senators (*Aligned Representative* and *Aligned Senators*). 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).[14] As locations differ in their treatment exposure, we employ a fixed effects within-estimation framework. Differences between years (e.g., due to differences in storm seasons, administrations, national election years, etc.) are captured by year fixed effects ($\tau_t$). Additionally, some structural differences between locations may have changed over the course of our 54-year-long panel, for example, altered patterns of storm occurrence due to climate change, mitigation efforts, county infrastructure, or population vulnerability. To account for such potentially nonlinear trends in unobserved factors in a flexible way, our baseline estimation includes county × decade fixed effects ($\sigma_i \times \zeta_t$). The results are also robust to applying state-specific damage proxies, county-specific linear time trends, and within-decade county-specific linear time trends (see Appendix Figure D4).

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 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

[13] Along with Figure D3, we explain the algorithm that we use to select the baseline *Wind Speed* polynomial based on a sequence of $F$-tests. 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.

[14] We show in Appendix Figure D4 that our results do not change significantly when we add a vector of lagged socioeconomic control variables and their interactions with the *Wind Speed* variables. There exists no systematic correlation with our main variables of interest and our results are robust to using a weighted sample balanced on pre-treatment characteristics.

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 subsamples of close election outcomes, where the alignment status is quasi-random (cf., e.g., Eggers et al., 2015; Marx et al., 2022; Pettersson-Lidbom, 2008).

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 within states. To account for both the correlation of our complex $Wind\ Speed^{b}_{i,t} \times Aligned\ Governor_{s,t}$ treatment within state-years, and potential serial correlation within counties, we cluster standard errors at the state × year and county level (cf. Kousky et al., 2018). Our results are robust to alternative choices of clustering the standard errors (including, e.g., the state, year, or hurricane level), applying spatial HAC-errors (Colella et al., 2019; Conley, 1999, cf. Appendix Figure D5), and permutation-based nonparametric inference based on placebo treatment allocation in the spirit of Chetty et al. (2009, see Section 4.2). Under all these alternative approaches to inference, we consistently reject the null hypothesis in the broad intermediate range of wind intensities that we show the relationship to be robust for.

# 4 Results

## 4.1 Heterogeneous Alignment Bias

Figure 2 shows the marginal effects of *Aligned Governor* for observing a disaster declaration at different levels of *Wind Speed*. The marginal effects, both in the polynomial (solid line) and the semi-parametric bin approach (dashed line), take a hump-shaped form with quantitatively similar point estimates.[15] 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 51 km/h (32 mph) in the polynomial estimation. These are typically non-catastrophic situations in which the president issues emergency declarations to ensure the functioning and quick repair of damaged crucial infrastructure or to organize local evacuations. Alignment effects peak at 132 km/h (82 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. Marginal effects decrease again for stronger wind speeds, becoming insignificantly different from zero for observations higher than 175 km/h (109 mph). Estimates for high wind speeds are less precise

[15] Likewise, alternative polynomials show similar results (Appendix Figure D3).

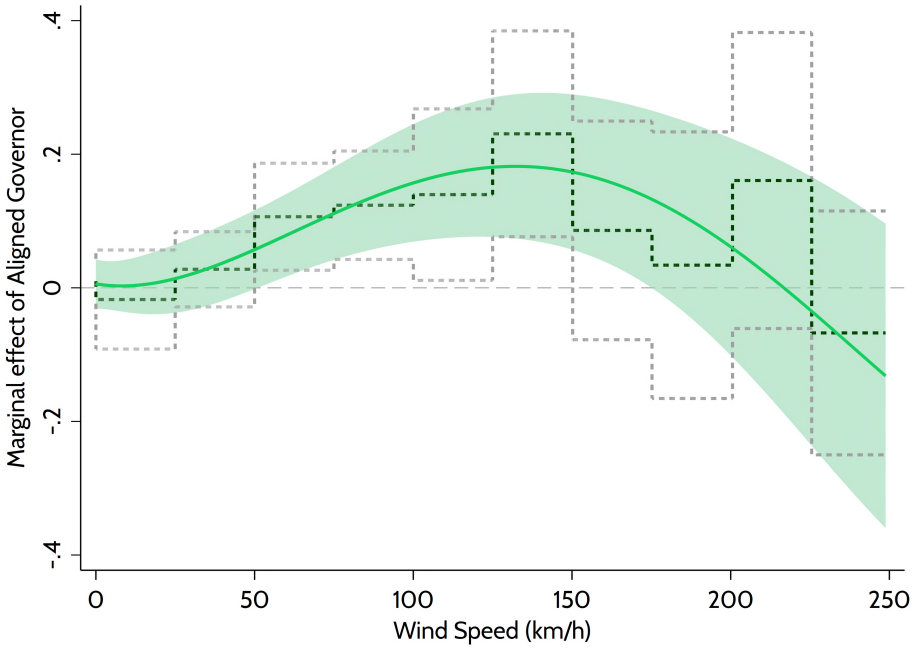


Figure 2: **Alignment Bias for Different Levels of *Wind Speed***

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. *Wind Class* 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. Note that the figure only displays marginal effects up to 250 km/h to facilitate graphical representation. Extreme observations with *Wind Speed* > 250 km/h are included in the estimation but only represent 0.1% of the sample. Both estimations include county-by-decade and year fixed effects. The light green shaded area and the dashed gray lines represent 95% confidence intervals applying two-way clustered standard errors on the state × year ($N_{sy} = 927$) and county level ($N_c = 1,136$). The sample covers 49,092 county-year observations affected by hurricanes in coastal states from 1965–2018.

due to the lower number of extreme events. The wind speed interval for which we can reject the null hypothesis that the alignment bias is equal to its estimated maximum extent at the 95% confidence level is *Wind Speed* < 67.58 km/h and > 219.12 km/h in the polynomial estimation and the wind speed bins below 50 and above 225 km/h for the semi-parametric approach.

Previous studies make strict functional form assumptions when analyzing political bias and usually estimate average effects; that is, treating all situations as equal in terms of potential exertion of political influence. However, the maximum marginal effect of 0.18 is about four times higher than the average bias over all wind speeds that we estimate in Appendix Table D6 for comparison. It corresponds to almost doubling the likelihood of a declaration for medium hurricane intensities (cf. Figure D1, Panel [b]), which underlines the scope of heterogeneity present in political effects. 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. Taking into account the distributions of

wind speed, declaration probabilities, population, associated per capita payments, and the estimated alignment bias, we calculate that the political component of direct hurricane relief amounts to roughly USD 400 million per year (see the supplementary explanations to Appendix Figure D6 for details). This corresponds to about 8.3% of the estimated total annual hurricane relief.

We examine the extent to which bias arises on the extensive and intensive margins. Extensive margin effects would mean that, being faced with the same medium-strength storm event, an aligned state would have a higher probability of receiving any declaration for a sub-group of affected counties. 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. Appendix Table D7 lends support to the intensive-margin channel, showing that the average wind speed of the least-affected county included in a declaration is about 15 km/h lower in aligned states. Hence, in situations where a county experienced intermediate damage and either decision would be politically justifiable, the importance of party affiliation increases and more likely becomes the factor to tip the scales.

## 4.2 Robustness

In Figure 3, 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 D5. We run a simulation in which we randomly reshuffle the alignment status between years within each state. This randomization provides a way to validate that our distinct hump-shaped pattern does not arise for placebo allocations of political alignment. For intermediate wind speeds, any of the 1,000 placebo marginal effects fall short of exceeding the estimated marginal effects using the actual alignment status (dashed line). Simulated marginal effects are close to zero for low and intermediate wind speeds but show more variation on the right, illustrating the higher uncertainty of our estimate for rare events with extreme damage. Calculating a permutation $p$-value based on this randomization inference approach, *Aligned Governor* has a positive and significant effect at the 95% confidence level in the *Wind Speed* interval $[52, 171]$ km/h, which is very close to the interval $[51, 175]$ km/h from applying conventional two-way clustering to the standard errors (see Figure 2).

To meet concerns of endogeneity in terms of unobserved factors that potentially systematically explain both alignment and declarations, we draw on subsamples of close-election outcomes. As political

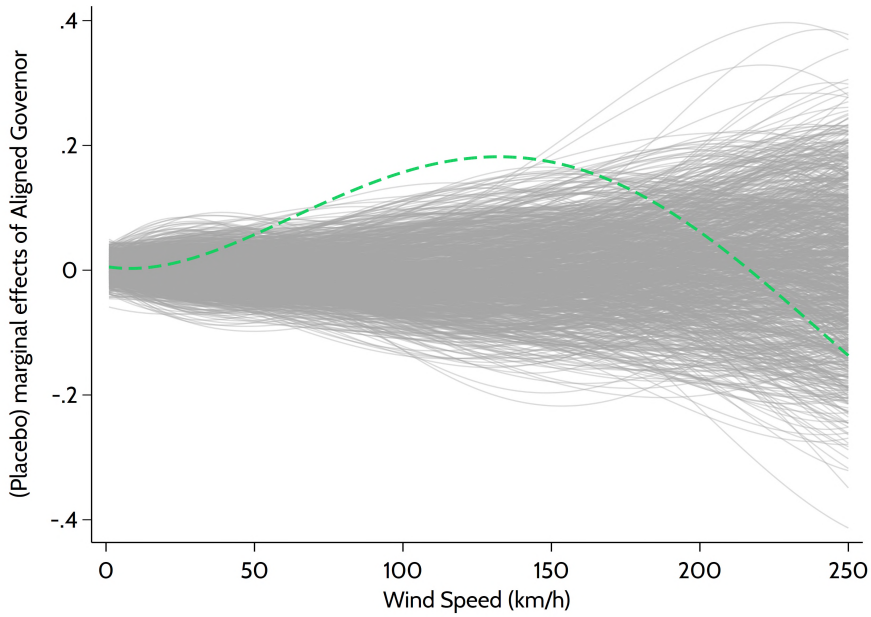


Figure 3: **Randomization Inference**

The thick dashed green line displays estimated marginal effects using the true data. The solid gray lines represent marginal effects from each of the 1,000 regressions with 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. Similar to the procedure for the synthetic control method (Abadie et al., 2015), we can calculate permutation $p$-values at every level of *Wind Speed*. We divide the number of runs for which the absolute value of the placebo alignment effect $\beta_{i,placebo}$ exceeds the estimated marginal effects $\beta$ using the true data at each *Wind Speed* by the total number of simulations $N$: $p_{perm.} = N^{-1} \sum_{i=i}^{N} \mathbb{1}[|\beta| < |\beta_{i,placebo}|]$. Based on this permutation test, *Aligned Governor* has a positive and significant effect at the 95% confidence level in the *Wind Speed* interval [52, 171] km/h.

alignment changes if a politician from the opposition party wins more votes than the incumbent in an election for one of the two offices, we can use small margins of victory to define situations in which governors are, quasi-randomly, just aligned or just unaligned with the president (cf. Akhtari et al., 2022; Brollo & Nannicini, 2012). Panels [a]–[c] of Figure 4 show that for very narrow margin-of-victory-bandwidths, the confidence interval for high wind speeds is wider, but 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 narrowly a governor won the previous election. Presidents might behave more generously in providing declarations and governors might exert more effort requesting relief if re-election is not certain. Panel [d] of Figure 4 distinguishes marginal effects of *Aligned Governor* by their electoral margin of victory. The effect is somewhat more pronounced and significant in a broader *Wind Speed* range for governors who won the previous election by a smaller margin.

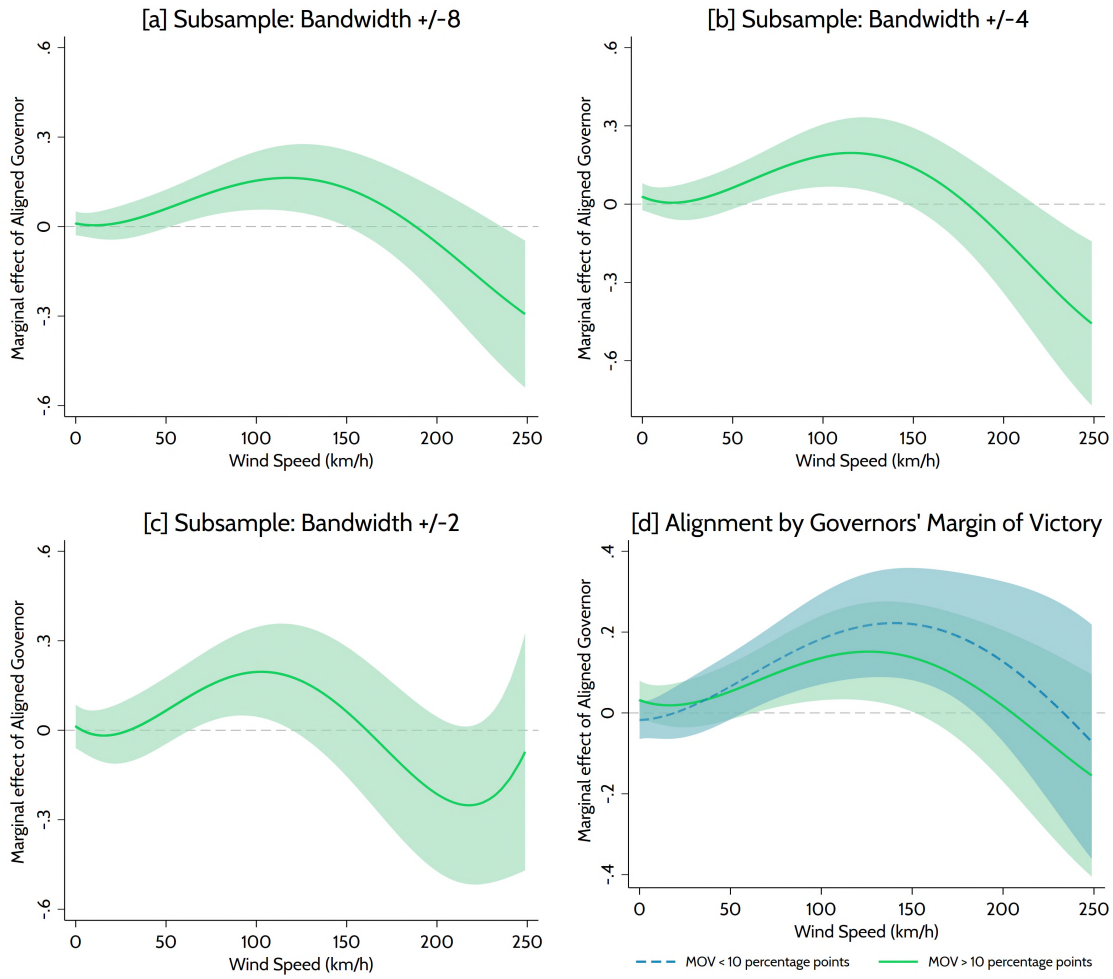


Figure 4: **Close-Election Subsamples and Governors' Margins of Victory**

Panels [a]–[c] show marginal effects of *Aligned Governor* in subsamples of close electoral outcomes in previous elections, where it is quasi-random whether a state is politically aligned or unaligned with the president. The figure shows results from three alternative close-election subsamples – defined by bandwidths of 2, 4, and 8 percentage points – as depicted in the panel titles. The bandwidth corresponds to half the difference in percentage points that would have been necessary to flip the alignment status, i.e., the margin of victory (MOV) of the most recent gubernatorial election or the MOV from the state that would have tipped the respective presidential election if this margin was closer. The estimation is otherwise identical to the baseline regression and uses a uniform kernel. Panel [d] displays results from one regression that distinguishes *Aligned Governor* by governors' MOV > 10 percentage points (solid green line) and MOV < 10 percentage points (blue dashed line). The shaded areas represent the 95% confidence interval applying two-way clustered standard errors on the state × year and county level.

A series of further sensitivity tests provides consistent support for the alignment bias. The hump-shaped effect exists when focusing on hurricane-intensity observations, excluding outliers or truncating extreme wind intensities (Appendix Figure D2), including additional controls for rainfall and storm surge, non-hurricane declarations, the number of hurricanes, party affiliation indicators, and ten lags of *Declaration* and *Wind Speed* (D4), in subsamples of swing states, emergency and major disaster declarations, and excluding individual states or decades (D7). We also show that differences in declaration behavior between aligned Republicans and Democrats are insignificant (D8).

## 4.3 Additional Heterogeneities: Stafford Act and Election Years

As explained in Section 2, the most important change in disaster relief legislature was the passage of the *Stafford Act* in 1988. Panel [a] of Figure 5 shows estimation results for the pre- and the post-1988 period. The alignment effect only plays a role in post-*Stafford Act* years. The *Stafford Act* increased the presidents' discretion to decide what qualifies for a declaration, creating the opportunity for more partisan decision-making. However, 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, including, for instance, relatively higher average intensity of hurricane seasons in the following decades (cf. Reeves, 2011).

To test whether a strategic-electoral motivation underlies our results, we analyze whether other political considerations matter and whether the alignment bias differs in election years. In Appendix Figure D8 we show evidence that, for medium-storm intensities, presidents issue more disaster declarations in electorally competitive states but less to states that are strongholds of the opposition, where the electoral incentives to "invest" political capital by issuing a borderline declaration are low. We also estimate the heterogeneous impacts of *Aligned Representative* and *Aligned Senators*. The results are statistically weaker, but, qualitatively, the same hump-shaped pattern emerges.[16]

Election years likely leverage the importance of alignment 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. Figure 5 represents triple-interaction results differentiating the marginal effect of *Aligned Governor* between non-election years and election years. Panel [b] focuses on presidential elections and Panel [c] adds congressional and gubernatorial election years. The relationship emerges in all years, but the alignment effect is higher in election years.

If declarations are partly electorally motivated, they might be more likely for storms occurring later in the season, closer to general elections in November, irrespective of political alignment. We additionally collected data on the month in which the strongest hurricane-related *Wind Speed* occurred in each county and year. *Hurricane Month* measures the number of months a hurricane occurred before November. It takes the value −1 if the strongest county-year *Wind Speed* occurred in October, −2 for September, −3 for August, etc. Panel [d] shows the marginal effects of *Hurricane Month* for different

[16] Congress members are not directly involved in the declaration process, but are known to lobby the president by writing supporting letters for governors' requests (Sylves, 2008, p. 91). The results in Figure D8 relate to findings in the distributive politics literature showing that areas with higher electoral support (Dynes & Huber, 2015; Larcinese et al., 2006) and presidents' co-partisan House members (Berry et al., 2010; Kriner & Reeves, 2015) receive higher government expenditures.

levels of *Wind Speed* by election years and non-election years. Only in election years, seasonality is positive and significant for a wide range of storm intensities, i.e., hurricanes of equal intensity have a higher probability of being declared a disaster if they occur in a later month of the hurricane season.

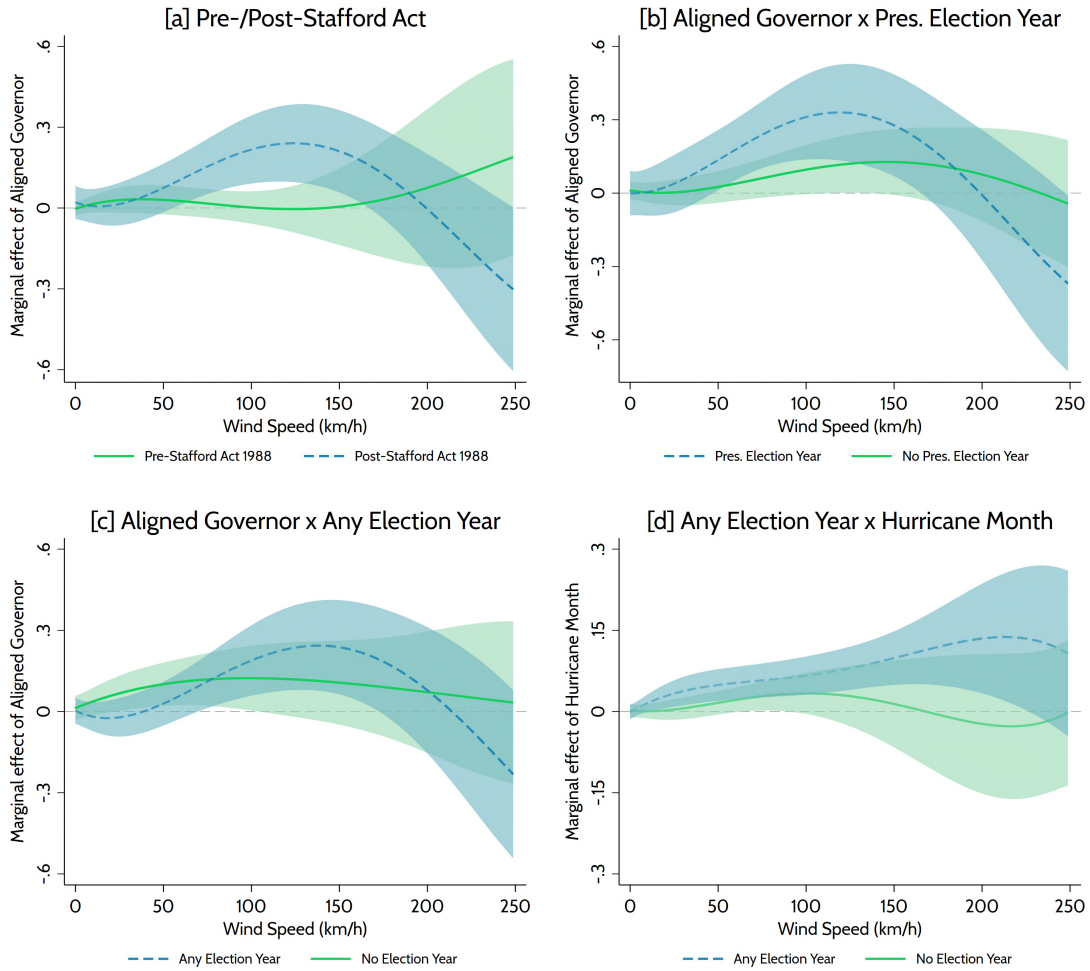


Figure 5: **Heterogeneous Political Effects and Electoral Cycles**

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 × year and county level. Panel [a] shows results from our main regression for the two subsamples before/after the Stafford Act in 1988. Panel [b] distinguishes marginal effects of *Aligned Governor* in presidential election years (dashed line) and non-presidential election years (solid line). Panel [c] distinguishes marginal effects of *Aligned Governor* in election years, including gubernatorial and congressional elections (dashed line), and non-election years (solid line). The specification in Panel [d] uses uses triple interactions of *Hurricane Month*, *Any Election Year*, and the *Wind Speed* polynomial (i.e., not conditioning on gubernatorial alignment status). Hence, Panel [d] displays marginal effects of *Hurricane Month* in election years (dashed line) and non-election years (solid line). *Hurricane Month* ranges from −6 (May) to 0 (November). For the triple interactions in Panels [b]–[d], we add the depicted variables of interest and all their possible cross-interactions with the *Wind Speed* polynomial to our baseline for the estimation of heterogeneous effects.

# 5 Conclusion

We demonstrate that disaster declarations in the United States involve a strongly heterogeneous political alignment bias. For extremely weak and strong hurricane intensities, there is no evidence for a political bias. After medium-intensity hurricanes, counties with a governor from the president's party have an up to 18 percentage points higher probability of receiving a federal disaster declaration. The alignment bias is most pronounced when the potential political returns are highest, e.g., in election years, which points at inefficiencies in the relief system. Heterogeneity analyses suggest that the passage of the *Stafford Act*, which augmented presidential discretion, led to a significant politicization of relief allocation in the recent 30 years. However, since we observe the outcomes of the declaration process as a whole, the alignment bias captures both "demand" (from the governors) and "supply side" effects (from the presidents).

Our results show that it is important to go beyond simple average estimates when analyzing discretionary decision-making that involves diverse situations regarding how obvious the appropriate decision or behavior is. Generally speaking, political influence may depend more on the specific constellations and opportunities that politicians face than previously revealed. Future research should evaluate whether our findings are generalizable to other political-economic contexts, e.g., for distributive policies where spending allocations involve a certain conditionality or eligibility criteria (cf., e.g., Budjan & Fuchs, 2021; Gehring & Schneider, 2018; 2020).

Our findings suggest several direct policy implications. First, technical improvements such as better satellite imagery would allow efficient data- and rule-based issuance of disaster declarations based on predefined disaster intensity thresholds, promoting fairness, predictability, and transparency.[17] Second, while some discretion might be desirable to ensure quick decision-making and disaster response, the presidents' decisions should require documented reasoning that increases political accountability. Third, a sensible approach might be to depoliticize disaster declarations and to assign declaration authority to a proficient bureaucrat (cf. Alesina & Tabellini, 2007; Bostashvili & Ujhelyi, 2019; Hessami, 2018).

Putting the way we deal with natural disasters to scrutiny is of particular relevance. Especially in many developing countries, a growing urban coastal population is projected to meet increasing disaster severity in the course of climate change. A key component to improving disaster resilience is an efficient disaster relief system. 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.

[17] Examples for such systems actually exist. Del Valle et al. (2020) and Tarquinio (2020) demonstrate how executing rule-based relief provision in Mexico and India improves the efficient allocation of resources and disaster recovery.

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# Appendix

Supplementary material for *Disastrous Discretion: Political Bias in Relief Allocation Varies Substantially with Disaster Severity*, by Stephan A. Schneider & Sven Kunze



## A Disaster Relief in the United States of America

If a severe disaster strikes, an affected state must activate its own emergency plan and local capacities first. Most natural disasters can be handled successfully without federal intervention by local or state means and the help of voluntary or non-governmental organizations. If the governor detects that local and state resources are insufficient to provide an effective response, they can request federal aid from the president.[18] The official request includes information from a preliminary damage assessment, a description of unmet needs and the state's efforts to cope with them, and an attestation that disaster response is beyond the state's capabilities (FEMA – EMI, 2017, Sylves, 2008, pp. 83–84). In the next step, the White House receives a recommendation from federal FEMA bureaucrats, but it is solely at the president's discretion whether to declare the event a disaster (Downton & Pielke Jr., 2001; FEMA, 2017a). Only contingent upon a presidential declaration, FEMA starts its managing work on site, determining necessary amounts of financial assistance and the individuals or entities eligible for relief. 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 Robert T. Stafford Disaster Relief and Emergency Assistance Act (*Stafford Act*) in 1988 emphasized the wide discretionary power of the president. As it does not contain a narrow definition of eligible events, it authorizes presidents to issue declarations in case of any natural catastrophic event and in any area for which they determine that federal relief is necessary (Gasper, 2015; Lindsay & McCarthy, 2015; Sylves, 2008).[19] Each presidential declaration is issued to a specific state and explicitly lists the counties

[18] To 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.

[19] Presidents 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). 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.

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).[20] 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.). As a supplement to local and state efforts, emergency declarations should ensure a quick response and functioning of essential services "to save lives and to protect property and public health and safety, or to lessen or avert the threat of a catastrophe" (Stafford Act, 1988). Emergency declarations have existed since 1974, and they are limited in scope, being restricted to USD 5 million for a single declaration. 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). 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).[21] 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 principle, 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.).[22]

## B Hurricane Data

Hurricanes constitute the most severe and destructive class of storms. A hurricane is a cyclonically rotating atmospheric low-pressure system with a typical diameter of the order of 500–700 km. Most hurricanes that affect the U.S. form over the Atlantic and make landfall in the states at the East Coast or the Gulf of Mexico.

[20] Sylves (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, 2017a).

[21] Federal assistance can be divided into public assistance (e.g., monetary, personnel, and technical assistance to public entities such as local governments), individual assistance (temporary housing, grants for repair and replacement of uninsured property currently up to USD 33,000, food coupons, crisis counseling, etc.), and hazard mitigation (funding for prevention of future risks) (DHS, 2018; FEMA, 2011; 2017b; Lindsay, 2014; Lindsay & McCarthy, 2015). For further summaries and explanations regarding the different spending programs see also Platt (1999), Schneider & Kunze (2022), and Sylves (2008). 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. Over the years, the largest number of supplemental spending bills have been passed in the event of hurricanes. Granting supplemental appropriations and regular replenishments of the DRF is the only way that the legislative branch is directly involved in the declaration process (ibid., p. 54). For a comprehensive overview on the DRF, see Schroeder (2018).

[22] This circumstance influences the choice of the main dependent variable. *Declaration* indicates the issuance of any hurricane-related declaration per county and year, hence not being prone to bias by double declarations for the same or multiple disasters (see Reeves, 2011). We also present results with a separate indicator for emergency and major disaster declarations.

To generate a proxy for hurricane damage, we adopt the tropical cyclone data assembled by Kunze (2021) with a higher resolution of $1 \times 1$ 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). To generate spatially varying wind speeds out of the IBTrACS raw data, we run the well-established Holland (1980) wind field model. The model is restricted to tropical cyclones above a raw data wind speed of 54 km/h and a maximum coastal distance of 500 km. It computes one-hourly asymmetric wind fields at a resolution of 0.01° (approximately 1 km) for every tropical cyclone in our sample. From these calculated wind fields, we take the maximum wind speed per county-year to construct our *Wind Speed* variable.

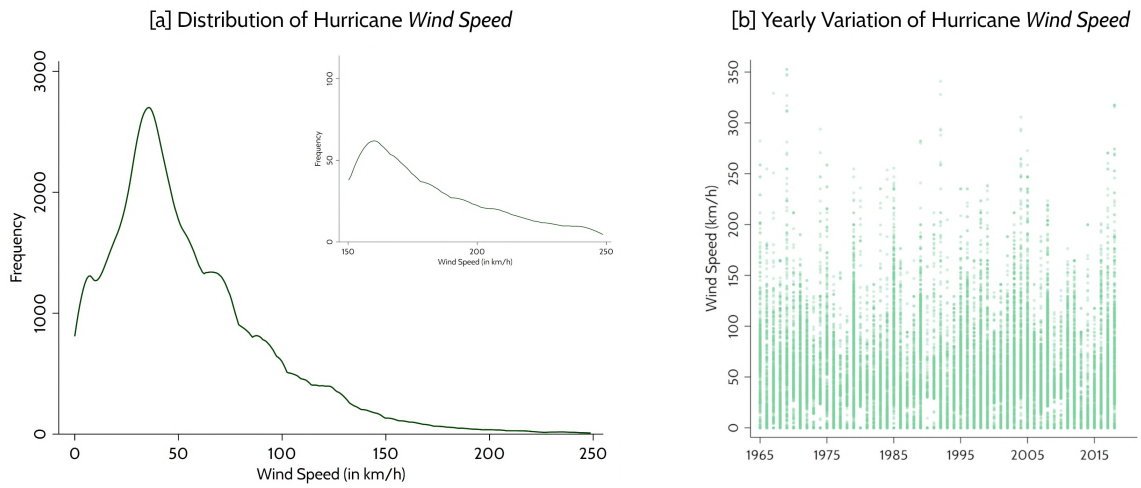


Figure B1: **Descriptive Statistics *Wind Speed***

Panel [a] shows the distribution of hurricane *Wind Speed* for 1965–2018. In Panel [b], each dot represents one county-year observation.

Figure B1 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. 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, including those further away from the storm center. 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 (Aguado & Burt, 2015, pp. 385–386).

In addition to wind speed, we also generate data on the two remaining damage sources of tropical cyclones, rainfall and storm surge. Weather station data on hurricane-related precipitation were provided by Roth (2018). We first 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. On a spatial $0.01° \times 0.01°$ grid, we match the data to individual counties. We keep the strongest precipitation value from each county in each year. 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 level for each tropical cyclone in the IBTrACS Knapp et al. (2010) data set is calculated. The

model runs at a spatial resolution of 0.1° and combines inputs from tides, bathymetry, tropical cyclones wind speed, and pressure drop fields in a hydrodynamic simulation using the DELFT3D software. Based on this model, we calculate the maximum inundation per county and year. We use the exposure to all three damage sources (hurricane wind speed, rainfall, and storm surge) to define our baseline sample.

The majority of the existing studies on the political economy of disaster relief predominantly uses reported damage measures from insurance data or databases such as EM-DAT or SHELDUS, which are prone to measurement errors, truncation, missing data, and endogeneity (cf. Felbermayr & Gröschl, 2014; Gallagher, 2021; Kousky, 2014).[23] In contrast, by modeling damage directly from meteorological hurricane intensity measures, we obtain a variable that is complete for our observation period (1965–2018), comparable over time, not prone to selection bias or missing values, not truncated, and exogenous.

## C Variable Description

*Declaration.* 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 tropical cyclone in their title or could be matched via the date of occurrence to storms in our storm 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. The declaration 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).

*Aligned Governor*. 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.

*Aligned Representative*. 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 (previous versions of this data set are used in Hainmueller et al. (2015) and Eggers et al. (2015)). For missing data and corrections, data from the CQ Voting and Elections Collection (https://library.cqpress.com/elections/) and https://ballotpedia.org/ were used.

*Aligned Senators*. 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.

*Wind Speed*. Maximum wind speed per county and year in km/h. Source: see Appendix B.

[23] Cole et al. (2012) is an exception in that regard as they use rainfall data from India.

*Rainfall*. Maximum tropical cyclone related rainfall in mm per county and year. Source: Roth (2018). For further details see Appendix B.

*Storm Surge*. Maximum storm surge water level in meters per county and year. Source: Kunze & Strobl (2020). For further details see Appendix B.

*Hurricane Month*. The month of the strongest tropical cyclone per county and year.

*Low-Support State President*. 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.

*State Competitiveness President*. 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).

*Presidential Election Year*. Indicator variable taking the value 1 in a presidential election year and 0 otherwise.

*Any Election Year*. 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).

*Population (log)*. Natural logarithm of population per county and year. Source: NBER.

*Black Population (log)*. Natural logarithm of black population per county and year. Source: https://seer.cancer.gov/.

*Real Income (log)*. Natural logarithm of income in current 1,000 USD per county and year. Source: U.S. Bureau of Economic Analysis (BEA).

*Per Capita Real Income (log)*. Per capita income in current USD per county and year. Source: U.S. Bureau of Economic Analysis (BEA).

*Public Assistance Projects*. Total number of public assistance projects in a county-year for declarations that include a public assistance program. Source: FEMA (2019).

*Total Public Assistance per Capita (log)*. Total amount of public assistance in a county-year for declarations that include a public assistance program. Source: FEMA (2019).

# D Additional Figures and Tables

**Declaration Denials and Relief Payments.** The data from FOIA request 2019-FEFO-0041 shows 142 county-year declaration denials related to hurricanes since 1992, which represents 2.5 percent of the reported requests (5,434 county-years received a declaration). As Table D1 shows, there were more declarations in aligned than unaligned county-years but also more denials from 1992–2018. According to this data, the share of county-years for which the White House officially rejects declaration requests for hurricanes is very low. However, this does not inform us about inofficial channels of communication, coordination on counties included in declaration requests, anticipatory behavior by governors, etc. We report the data for completeness and include them in our replication package to inform future research about data availability at the time of writing. Due to the potential flaws, we refrain from a closer analysis and interpretation.

Table D1: **Declarations and Denials (1992–2018)**

| | Total | Aligned | Unaligned |
|---|---|---|---|
| Declarations | 5,434 | 2,932 | 2,502 |
| Denials | 142 | 125 | 17 |
| Denial-Declaration-Rate | 0.025 | 0.041 | 0.007 |

The table summarizes information on declarations and denials by alignment status since 1992. "Declarations" and "Denials" display the respective number of county-years that have received a hurricane-related disaster declaration or have been rejected, respectively. "Denial-Declaration-Ratio" displays the ratio of denials to declarations.

Table D2: **Declaration Probabilities – Raw Data**

| | Obs. | Decl. Prob. |
|---|---|---|
| <25 km/h | 24,911 | 0.028 |
| 25–50 km/h | 10,439 | 0.091 |
| 50–75 km/h | 6,358 | 0.17 |
| 75–100 km/h | 3,521 | 0.215 |
| 100–125 km/h | 1,898 | 0.334 |
| 125–150 km/h | 1,059 | 0.415 |
| 150–175 km/h | 421 | 0.684 |
| 175–200 km/h | 235 | 0.791 |
| 200–225 km/h | 120 | 0.850 |
| >225 km/h | 130 | 0.931 |

The table lists the number of observations and average probability to observe a disaster declaration by *Wind Speed* interval.

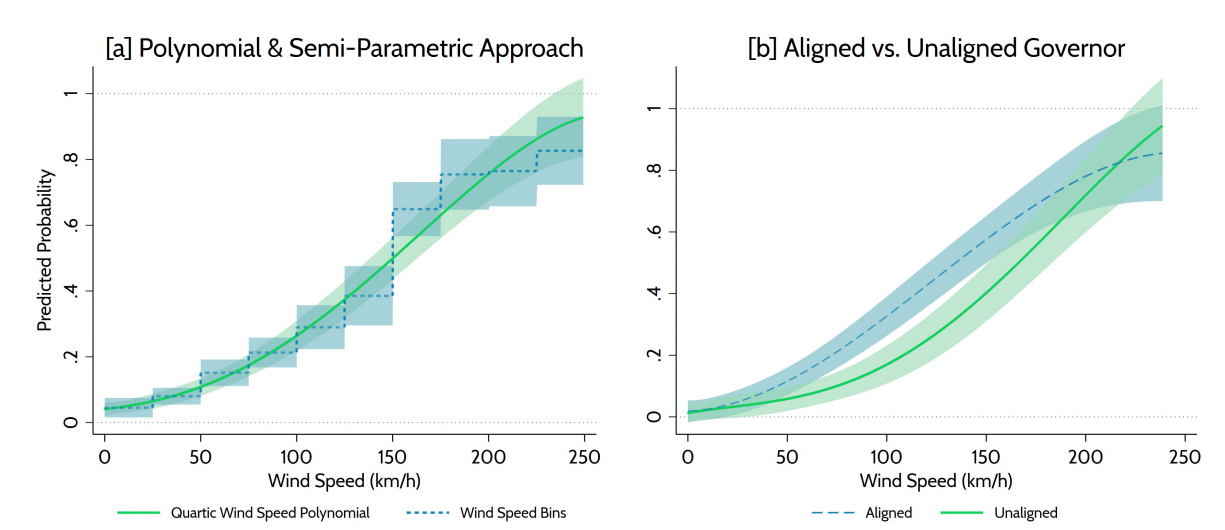


Figure D1: **Probability of Disaster Declaration for Different Wind Intensities**

Panel [a] shows the predicted probabilities for a disaster declaration from two different estimations with *Wind Speed* as the explanatory variable. The specification represented by 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 year fixed effects and county × decade fixed effects. Panel [b] 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 in both panels show 95% confidence intervals applying two-way clustered standard errors on the state × year and county level.

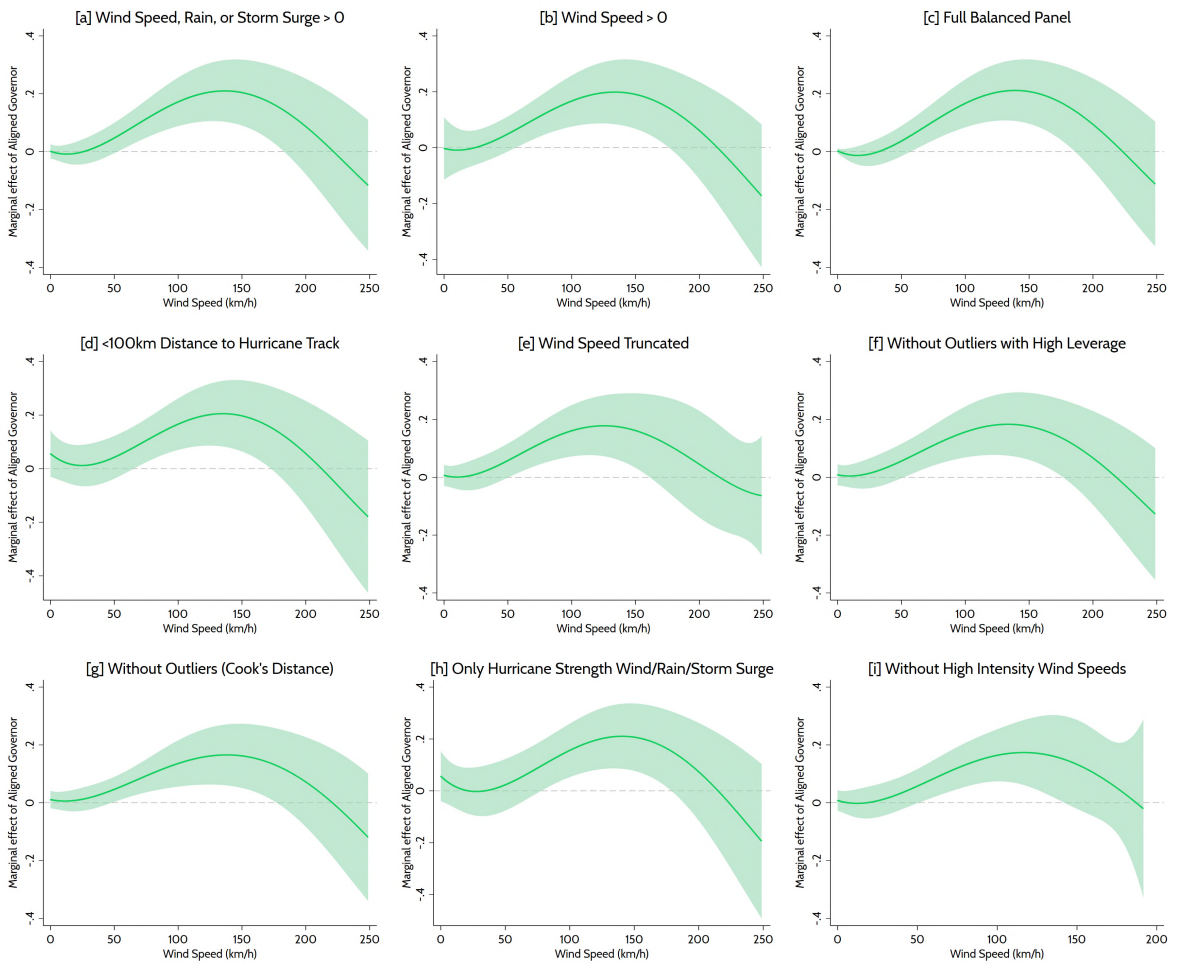


Figure D2: **Robustness – Alternative Sample Definitions**

This figure shows the sensitivity of our results to alternative sample definitions and in various subsamples. All 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 × 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*. In Panel [d], county-year observations are restricted to those within maximum distance of 100 km to the main track of a hurricane. Panel [e] truncates *Wind Speed* at 250 km/h. Panel [f] excludes all observations above a leverage of $(2k + 2)/n$. Panel [g] excludes all observations with a higher Cook's distance measure of $4/n$. Panel [h] restricts the sample to observations with hurricane intensities in *Wind Speed*, *Rainfall*, and *Storm Surge*, following the composite hurricane category scale by Bloemendaal et al. (2021), which defines category 1 as wind speed >119 km/h (corresponding also to the Saffir-Simpson-Scale), accumulated rainfall >100 mm, and storm surge >0.75 m. Panel [i] excludes all observations with wind speeds above the 99% percentile (192 km/h).

Table D3: **Summary Statistics**

| | Observations | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| *Declaration* | 49,092 | 0.11 | 0.31 | 0.00 | 1.00 |
| *Emergency Declaration* | 49,092 | 0.05 | 0.22 | 0.00 | 1.00 |
| *Major Declaration* | 49,092 | 0.09 | 0.29 | 0.00 | 1.00 |
| *Aligned Governor* | 49,092 | 0.44 | 0.50 | 0.00 | 1.00 |
| *Aligned Representative* | 49,092 | 0.46 | 0.50 | 0.00 | 1.00 |
| *Aligned Senators* | 49,092 | 0.29 | 0.46 | 0.00 | 1.00 |
| *Wind Speed* | 49,092 | 34.55 | 41.77 | 0.00 | 352.71 |
| *Hurricane Month* | 48,808 | -2.74 | 1.39 | -6.00 | 0.00 |
| *Low-Support State President* | 49,034 | 0.03 | 0.17 | 0.00 | 1.00 |
| *State Competitiveness President* | 49,034 | 42.46 | 6.02 | 12.86 | 50.00 |
| *Presidential Election Year* | 49,092 | 0.24 | 0.43 | 0.00 | 1.00 |
| *Any Election Year* | 49,092 | 0.56 | 0.50 | 0.00 | 1.00 |
| *Presidents' First Term* | 49,092 | 0.67 | 0.47 | 0.00 | 1.00 |
| *Swing State President* | 49,064 | 0.62 | 0.48 | 0.00 | 1.00 |
| *Population (log)* | 49,026 | 10.51 | 1.36 | 3.69 | 15.36 |
| *Black Population (log)* | 45,654 | 8.23 | 2.17 | 0.00 | 13.80 |
| *Real Income (log)* | 43,909 | 13.80 | 1.57 | 7.72 | 19.52 |
| *Per Capita Real Income (log)* | 43,909 | 10.16 | 0.39 | 8.75 | 12.12 |

**Wind Speed Polynomial**. As Figure D3 shows, our results are robust to including higher order polynomials up to ninth degree. The selection of the quartic *Wind Speed* polynomial for the baseline model is derived from a sequence of $F$-tests. To 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. Table D4 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.

Table D4: **Sequential *F*-Tests Polynomials**

| | $F$-statistic | $p$-value |
|---|---|---|
| 9 vs 8 | 0.22 | 0.80 |
| 8 vs 7 | 0.33 | 0.72 |
| 7 vs 6 | 2.32 | 0.10 |
| 6 vs 5 | 2.16 | 0.12 |
| 5 vs 4 | 0.62 | 0.54 |
| 4 vs 3 | 3.25 | 0.04 |
| 3 vs 2 | 10.05 | 0.00 |

The table displays the results of seven $F$-tests based on our polynomial regression model presented in the paper. We test the model of polynomial degree $n$ against the 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*.

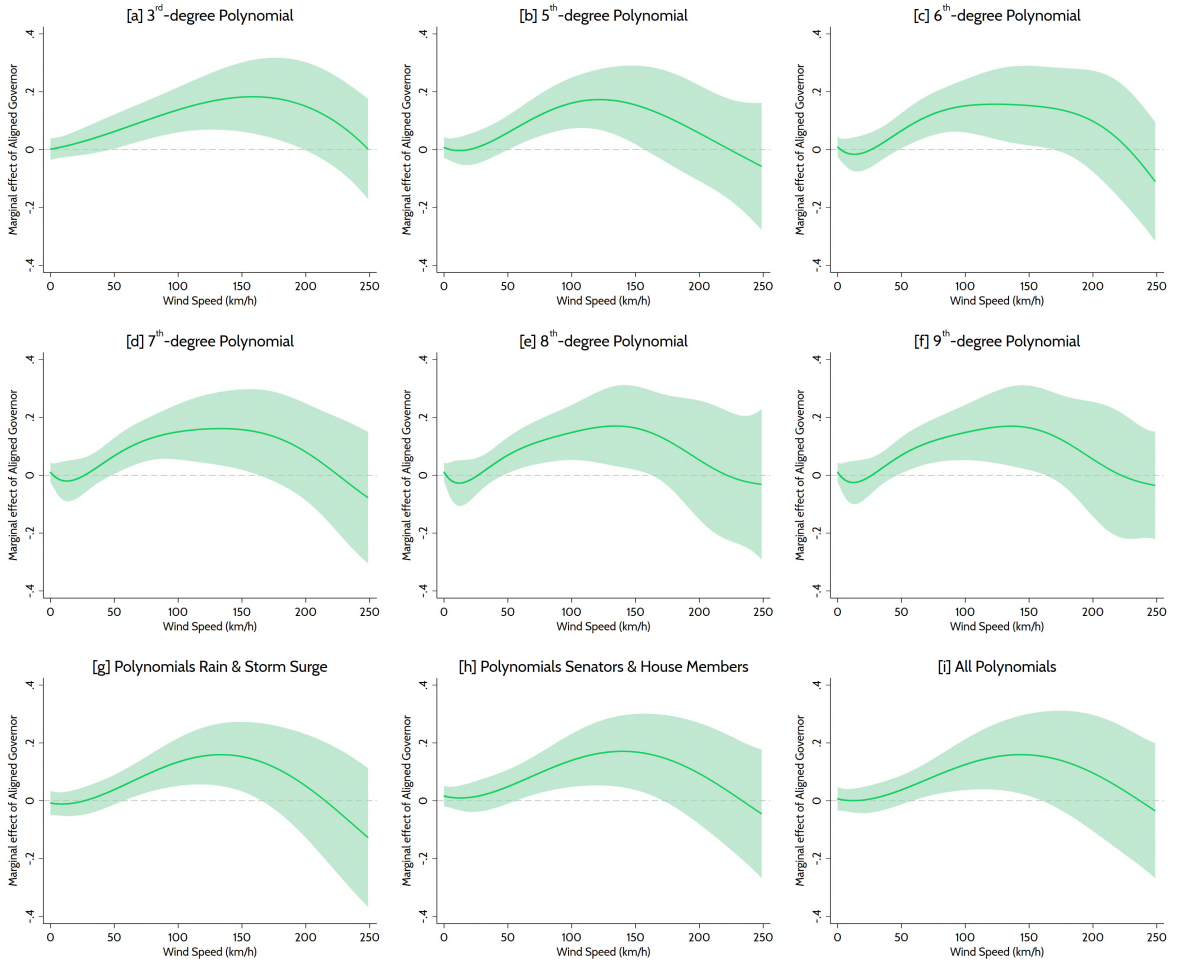


Figure D3: **Robustness – Alternative Polynomials**

Panels [a]–[f] show the sensitivity of our main result to applying different polynomial degrees of *Wind Speed* as indicated in the panel titles. Panels [g]–[i] allow for additional polynomial interactions. Panel [g] includes additional polynomial interactions of *Aligned Governor* with *Rainfall* and *Storm Surge* and Panel [h] adds polynomial interactions of *Wind Speed* with *Aligned Representatives* and *Aligned Senators* to the baseline. Panel [i] allows for all interactions as described in Panels [g] and [h]. All 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 × year and county level. The sample covers county-year observations from 1965–2018.

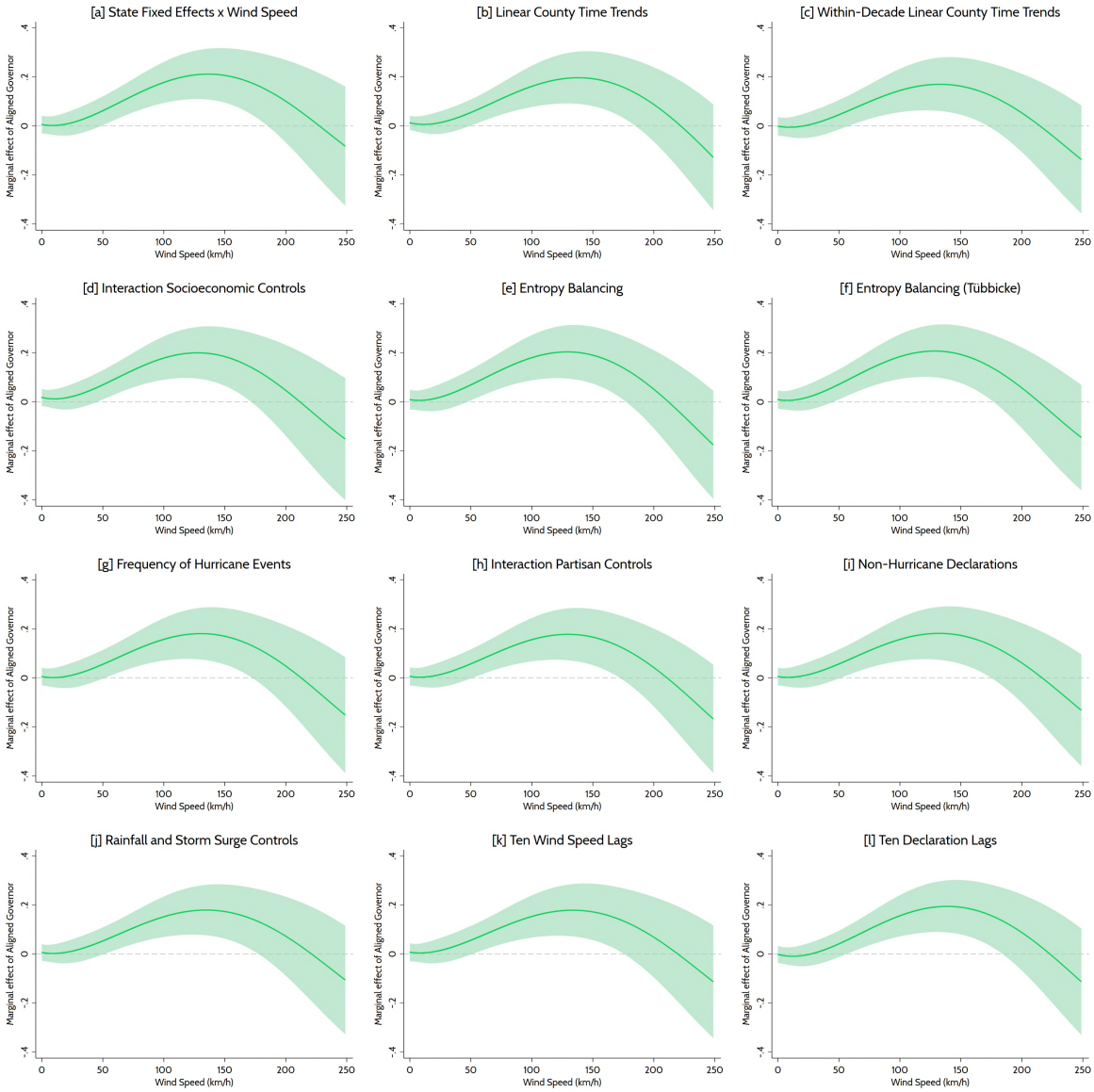


Figure D4: **Robustness – Alternative Specifications**

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 × 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 to demonstrate that our results do not depend on the assumption of a nationwide uniform resilience level. Panel [b] replaces county × 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. In Panel [d] the estimation includes *Population (log)*, *Black Population (log)*, *Real Income (log)*, *Per Capita Real Income (log)*, all lagged by one year, and their interactions with the *Wind Speed* polynomial. In Panels [e] and [f], observations are weighted to obtain a sample that is balanced on the set of the aforementioned socioeconomic covariates and *Wind Speed*. The weights are obtained from different procedures of entropy balancing (explanation see below). Panel [g] controls for the frequency of hurricane *Wind Speed* occurrence within a county-year. Panel [h] includes the interaction of a party affiliation indicator for Democrats with the *Wind Speed* polynomial. Panel [i] adds a dummy taking the value 1 if there was at least one non-hurricane related disaster declaration in a county-year. Panel [j] controls for *Rainfall* and *Storm Surge*. Panels [k] and [l] display the robustness of our main result to controlling for long, persistent past hurricane shocks and declarations. Panel [k] controls for ten lags of *Wind Speed* and Panel [l] adds ten lags of *Declaration*.

**Notes on Covariate Balancing.** In Table D5 and in a previous version of this paper (Schneider & Kunze, 2022), we show that there exists no systematic relationship regressing pre-hurricane socioeconomic variables on our main variables of interest, conditional on the same set of controls and fixed effects. Nonetheless, to further alleviate concerns about the correlation of alignment with observable characteristics, we demonstrate that the estimates in our quasi-experimental setting are insensitive regarding corrections of potential covariate imbalance. We deploy entropy balancing to preprocess our data set in order to obtain a sample balanced on observables. The entropy balancing algorithm directly yields balancing scalar weights for each observation, which fulfill the specified balancing constraints but staying as close as possible to unit weights. These weights can be used to run regressions on a balanced sample (Hainmueller, 2012; Tübbicke, 2021). Entropy balancing has been developed for binary treatments and there exists a novel extension for continuous treatments by Tübbicke (2021), 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. We balance the sample on the alignment indicator regarding the full set of controls (socioeconomic and hurricane-related covariates). We apply the resulting weights to run a weighted version of our baseline regression (see Figure D4, Panels [e] and [f]). Weighted regressions yield results that are very similar to our baseline.

Table D5: **Regression Results – Balance Test**

| | *Population (log)$_{t-1}$* | *Real Income (log)$_{t-1}$* | *Per Capita Real Income (log)$_{t-1}$* | *Black Population (log)$_{t-1}$* | *Aligned Governor* |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Wind Speed (St. Dev.)* | 0.005 | 0.006 | -0.000 | -0.002 | 0.001 |
| | (0.004) | (0.004) | (0.002) | (0.006) | (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 × 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.

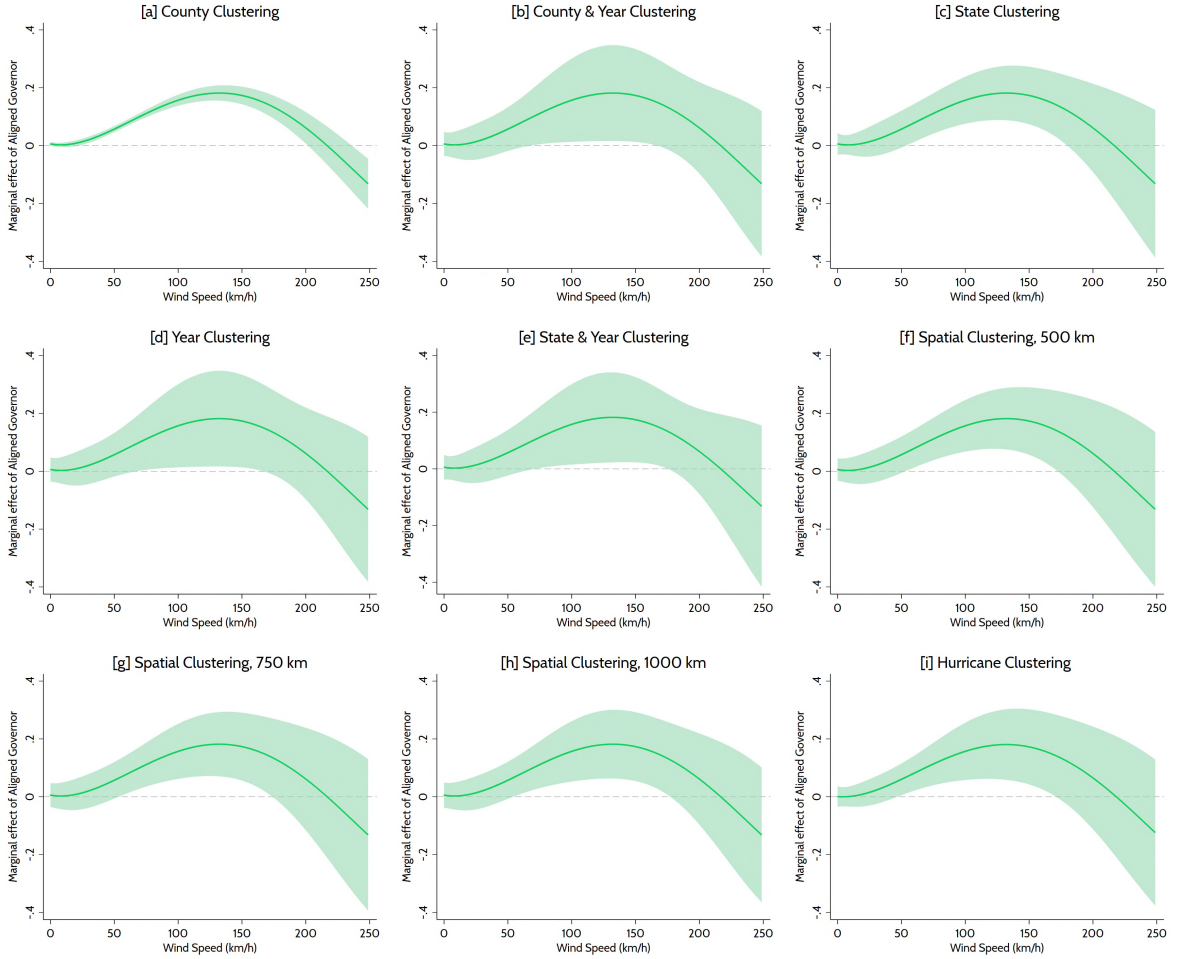


Figure D5: **Robustness – Alternative Clustering Choices**

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. Panel [i] clusters standard errors by counties affected by hurricanes. 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.

**Average Alignment Effect.** To better understand the magnitude and economic significance of the heterogeneous political alignment bias, we run estimations that – comparable with the literature – estimate an average alignment bias for all situations. Table D6 shows the estimates from six fixed effects regressions explaining the issuance of disaster declarations. The estimations do not account for the flexible interaction of *Aligned Governor* and the *Wind Speed* polynomial but otherwise take the same form as our baseline:

$$Declaration_{i,t} = \alpha + \beta Aligned\ Governor_{s,t} + \gamma Wind\ Speed_{i,t} + \boldsymbol{X}'_{i,t}\mu + \tau_t + \sigma_i \times \zeta_t + \varepsilon_{i,s,t}. \quad (2)$$

A one standard deviation increase in *Wind Speed* (approx. 40 km/h) raises the probability of a disaster declaration by about 10 percentage points. The following columns add our main variable of interest, *Aligned Governor*. The estimated coefficients are highly significant in all regressions. Counties have, on average, a 4.2–5.1 percentage point higher chance of receiving a disaster declaration if the president and the governor are aligned.

Table D6: **Regression Results – Average Estimates**

| Dep. var.: *Declaration* | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Aligned Governor* | | 0.051 | 0.046 | 0.044 | 0.043 | 0.042 |
| | | (0.019) | (0.019) | (0.020) | (0.020) | (0.020) |
| *Aligned Representative* | | | 0.019 | 0.024 | 0.025 | 0.024 |
| | | | (0.007) | (0.009) | (0.009) | (0.009) |
| *Aligned Senators* | | | 0.026 | 0.040 | 0.043 | 0.041 |
| | | | (0.022) | (0.033) | (0.033) | (0.033) |
| *Wind Speed (St. Dev.)* | 0.109 | 0.109 | 0.109 | 0.110 | | |
| | (0.008) | (0.008) | (0.008) | (0.009) | | |
| County × decade FE | | | | X | X | X |
| *Wind Speed* polynomial | | | | | X | |
| *Wind Speed* bins | | | | | | X |
| 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. *Wind Speed* is shown in standard deviation increases (above zero) which is 40.59 km/h. 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. "Dep. var. mean" denotes the mean of the dependent variable. The sample runs from 1965–2018 in all regressions.

We draw a comparison to the political economy literature on the allocation of U.S. federal spending. Analyzing a wider range of federal funds, the results of Larcinese et al. (2006) correspond roughly to a 2.7% increase in federal funding due to gubernatorial alignment with the president. Albouy (2013), Berry et al. (2010), and Kriner & Reeves (2015) all find increases in the order of 4% for aligned federal politicians in high-variation government spending programs. Although accurate comparisons of studies are impossible due to the different spending categories, our average estimate indicates a similar magnitude. However, if we account for the nonlinear nature of the relationship, we find a substantially higher political and economic relevance. At its maximum, the 18 percentage point alignment effect corresponds to a doubling of the declaration probability.

**Relief Amounts and Political Share of Disaster Relief.** To calculate the political share of the annual relief amounts associated with hurricane-related disaster declarations, 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. We use real 2015-US dollars to allow for comparability over time. Our calculations assume that relief payments are, *ceteris paribus*, proportional to county populations. 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 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 events require disproportionately high relief payments.

**2a.** The distribution of wind speeds is skewed (cf. Appendix Figure B1). I.e., low wind speed observations occur much more frequently than extreme ones, which cause the highest payments. We derive the annual average distribution of wind speeds using a nonlinear density estimate.

**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 D1). 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 multiply this prediction curve with the average affected population, which we obtain from a regression of county population on our *Wind Speed* polynomial.
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. 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 D6) 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 D6) 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. Approximately 8.3% of the FEMA payments (~USD 400 million) are attributable to political alignment.

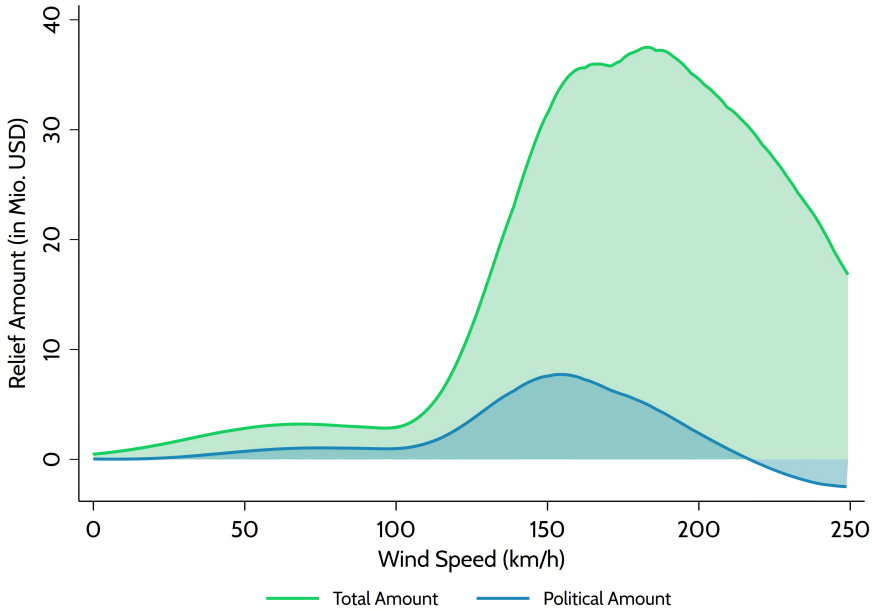


Figure D6: **Total Relief Amounts and Share Associated with Political Bias**

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. Note that this figure only contains FEMA's public assistance and individual assistance. It does not account for other spending categories such as hazard mitigation or differences in long-term costs due to the presence or absence of initial relief and potential indirect payments.

**Intensive Margin.** Table D7 contains the regression results discussed at the end of Section 4.1.

Table D7: **Regression Results – Intensive Margin**

| Dep. var.: *Lowest Wind Speed in Declaration* | (1) | (2) |
|---|---|---|
| *Aligned Governor* | -15.994 | -16.634 |
| | (7.290) | (6.105) |
| *Aligned Representative* | | 3.410 |
| | | (5.079) |
| *Aligned Senators* | | -13.992 |
| | | (4.696) |
| Additional controls | | X |
| Dep. var. mean | 41.573 | 39.687 |
| Observations | 227 | 210 |

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. Column 2 adds the set of lagged socioeconomic variables (*Population*, *Black Population*, *Real Income*, and *Per Capita Real Income*) and maximum *Wind Speed* in a respective state-year as control variables. 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.

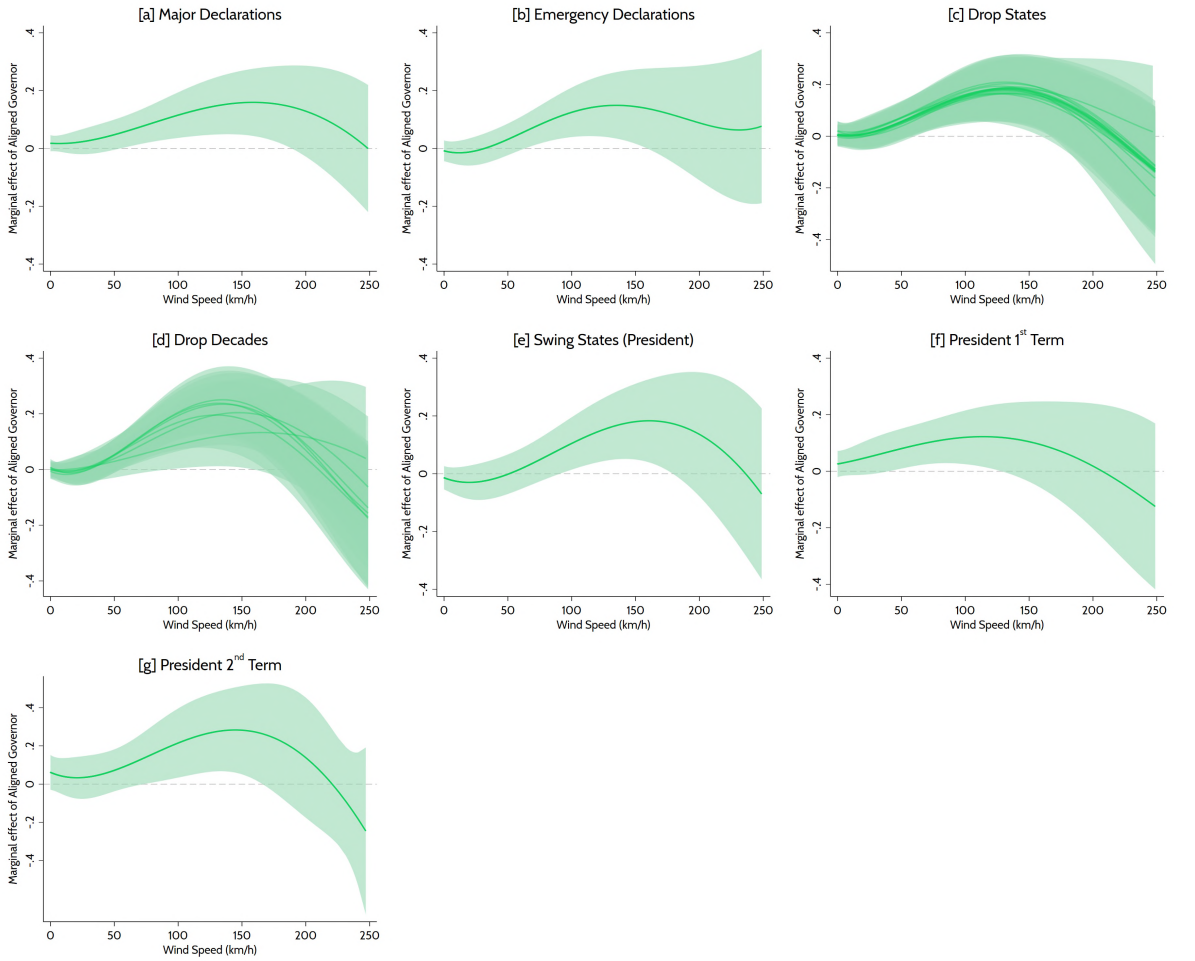


Figure D7: **Robustness – Alternative Dependent Variables and Further Subsamples**

The figure displays marginal effects of *Aligned Governor* for different levels of *Wind Speed*, derived from our polynomial estimation (solid green line). The light green shaded area represents the 95% confidence interval applying two-way clustered standard errors on the state × year and county level. In Panel [a], the dependent variable is *Major Declaration* and in Panel [b] *Emergency Declaration*. Panels [c] and [d] show the sensitivity of our result to the omission of groups of observations. They display marginal effects of *Aligned Governor* from individual regressions, where each regression omits all observations from one of the 18 coastal states [c] or six decades [d] covered by our baseline sample. The panels show separate lines for the predicted marginal effects from each regression. Panel [e] 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 [f] restricts the sample to observations of presidents in their first electoral term. Panel [g] restricts to the second electoral term, respectively.

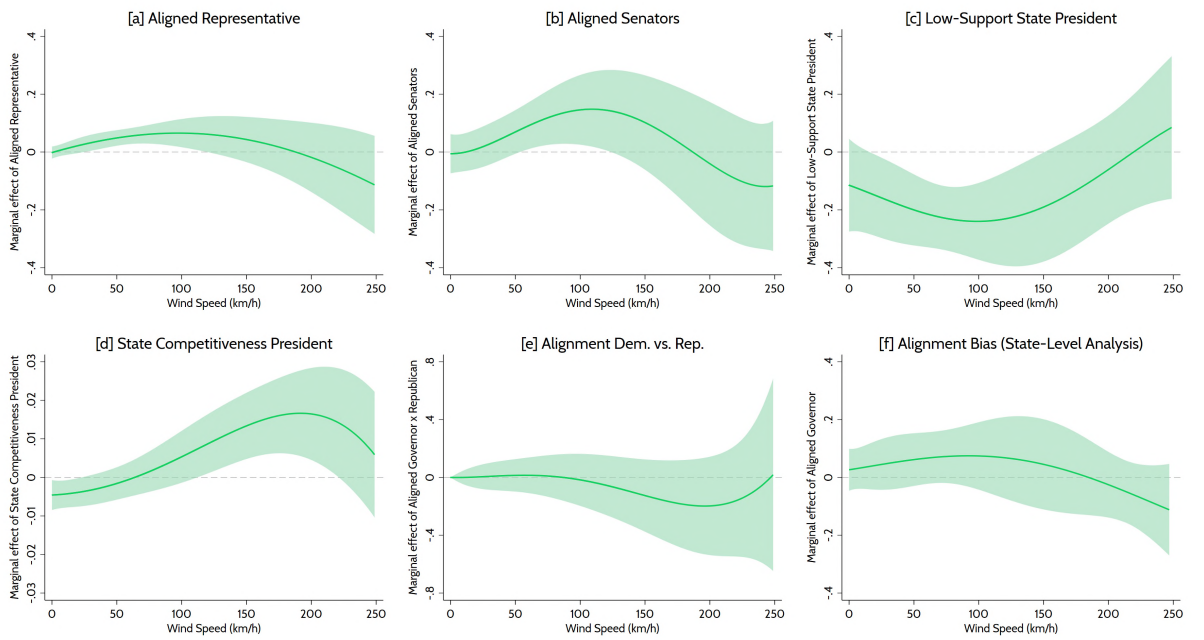


Figure D8: **Further Political Factors**

The figure displays marginal effects for the variables of interest depicted on the vertical axes 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 × year and county level. Panels [a] and [b] plot the marginal effect of having an *Aligned Representative* and two *Aligned Senators*, respectively. Panel [c] shows marginal effects of being in a state with low electoral support for the incumbent president's party (less than 40% of the vote share in the previous election). *Low-Support States* have a significantly lower probability to receive a disaster declaration for low to medium wind speeds. Panel [d] shows marginal effects for electoral competitiveness, where 50 represents a zero margin of victory of the president in the previous election and hence maximum competitiveness, while 0 implies that the president received all votes. Competitive states received more disaster declarations for medium to high storm intensities. Panel [e] shows differences of *Aligned Governor* between Democrats and Republicans from triple interactions, using an indicator for Republicans. Differences are insignificant for all storm intensities. The data for the estimation in Panel [f] are aggregated at the state level to investigate a potential extensive-margin mechanism. 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.

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