Bureaucracy and Political Bias: Evidence from Floods*

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Abstract

We study whether bureaucrats preemptively reflect the executive politician's preferences in their decisions. Combining novel administrative data from the Federal Emergency Management Agency (FEMA) with hydrological models, we find that a standard deviation decrease in a county's alignment with the president leads to a 4 percentage point drop in the probability of bureaucrats flagging a county as requiring federal aid following an average-sized flooding event. This bias disappears in the most severe floods. We find evidence suggesting that such biases are significantly reduced when a career civil servant is overseeing the bureaucratic process rather than a political appointee.

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1 Introduction

In many countries, economic development is accompanied by the establishment of bureaucracies as apolitical bodies, with the adoption of rule-based hiring and professionalization of the civil service workforce (Weber, 1922; Besley et al., 2022; Spenkuch et al., 2023; Aneja and Xu, 2024). Despite such attempts to insulate the bureaucracy from political influence, the final decisions on the allocation of government resources are frequently described as exhibiting political bias in service of the incumbent executive politician, both in the United States (Kriner and Reeves, 2015; Potter, 2025) and elsewhere (Hodler and Raschky, 2014; Asher and Novosad, 2017). But efforts to reduce these biases raise a key question: Are such biases the result of direct political pressure, or do bureaucrats act preemptively in anticipation of the politician's preferences? Answering this question is challenging because internal agency decision-making processes are rarely observable, and even when they are, there are no external metrics to compare the outcomes against.

We overcome these challenges in two ways. First, we focus on an administrative feature of the U.S. Federal Emergency Management Agency (FEMA) disaster aid process that allows us to observe the FEMA bureaucrats' intermediate decisions. The administrative process, called the Preliminary Damage Assessment (PDA), reflects the bureaucrats' assessment of which counties are in need of federal aid in disaster recovery–*prior* to the president's involvement in making final decisions on disaster declaration and aid allocation. Second, in order to assess political biases in the bureaucrats' estimates, we focus on flooding events and use a ground-truthed hydrological model to develop a benchmark metric of flooding intensity. We then test whether counties politically misaligned with the incumbent president are *less* likely to be included in the list of counties in need of federal support, *controlling for* the independently-developed metric of flooding intensity. Our novel administrative data, combined with the hydrological model, allow us to observe whether the incumbent president's preferences are preemptively reflected in the bureaucratic decision-making process.

In addition to being an ideal setting for investigating the sources of political bias, our evaluation of the FEMA disaster process comes against the backdrop of rapid climate change, which increases the frequency and intensity of natural disasters (Mendelsohn et al., 2012; Marsooli et al., 2019). Spending on such hazards makes up a large fraction of overall governmental spending, with nearly 20% of the Department of Homeland Security's annual budget allocated to FEMA's disaster relief fund alone in 2023 (U.S. Department of Homeland Security, 2022). In particular, flooding is the most common of these natural disasters, resulting in an average of $46 billion per year in damage over the past 10 years, impacting all states across the country (Congressional Budget Office, 2025). A county receiving disaster aid for floods on average receives $1.3 million (in 2023$) in funding for recovery. With an increasing share of the US population potentially at risk from natural disasters such as floods, the importance of unbiased and accurate allocation of federal disaster aid is likely to grow.

Our results indicate that flooding intensity does contribute significantly to the probability that bureaucrats include a county in their PDA, and therefore indicate it as in potential need of federal aid. Nevertheless, a one standard deviation decrease in the vote margin in favor of the president leads to a 4 percentage point drop in the probability of the county being included in the PDA for a flood of average intensity. Such bureaucrat-driven "alignment bias" becomes smaller and eventually disappears as the flooding intensity increases; our coefficient estimates suggest that the political biases are no longer relevant for the strongest flooding events. Furthermore, we find evidence suggesting that the bias at the bureaucratic stage explains a large part of the bias observed in the final, actual allocation of disaster aid. To the extent that the PDAs are driven by FEMA bureaucrats, this points to how bias in service of the incumbent president arises early in the process, prior to the president's direct involvement.

We find additional results suggesting FEMA bureaucrats' preemptive political bias in favor of the incumbent president. First, while our main results focus on bias at the extensive margin (inclusion of counties in PDAs), we find similar biases at the intensive margin, with bureaucrats reporting that counties misaligned politically with the president are relatively less in need of financial assistance. Second, we do not find similar patterns of political bias when we study the vote margin in favor of the incumbent state governor, supporting our conclusion of the bias being aligned with the executive branch. Crucially, our results are robust to the use of alternative flooding intensity metrics, the inclusion of time-varying county-level covariates, and alternative identification strategies (relying on quasi-random variations in vote returns from "close elections," *à la* Lee, 2008).

Under what circumstances do FEMA bureaucrats preemptively comply with the president's political preferences? We find evidence suggesting that these political biases are significantly smaller when a career bureaucrat is overseeing the PDA process. In contrast, biases are not significantly reduced in PDAs overseen by non-career executives appointed through presidential nomination. Consistent with the importance of the PDA process taking place in the immediate aftermath of the disaster, we do not find significant effects from congressional oversight committees. We additionally fail to find evidence suggesting that such political bias is driven by the balance on FEMA's annual disaster relief budget, the incumbent president's party, or the counties' political importance in the most recent presidential election prior to the disaster. An inspection into different *categories* of disaster aid suggests that the biases are driven by expenditures likely more open for executive discretion (e.g., spending on "protective measures"), versus expenditures on "debris removal" showing no significant political bias.

The study speaks to a rapidly expanding literature on the interaction between politics and the performance of public institutions. Our results on the role of career appointees speak to the importance of apolitical hiring on public sector performance (Aneja and Xu, 2024). In addition, the failure to find association between non-career, politically appointed, executives and lower political bias (unlike career civil servants in leadership positions) is consistent with such appointments being largely partisan (i.e., politically aligned with the president) in their nature (Spenkuch et al., 2023). Further, to the extent that FEMA bureaucrats are explicitly directed to be "as thorough and comprehensive as possible (FEMA, 2025c)" in their PDAs, our use of hydrological models as a benchmark measure of FEMA bureaucrats' accuracy sheds light on how environmental models can be used to evaluate public sector performance. Evaluating such performance is typically challenging due to the multidimensional nature of bureaucratic tasks (Dixit, 2002; Decarolis et al., 2020).

We also contribute to the limited empirical literature on the political economy of FEMA, its disaster declaration process, and its subsequent aid dispersion (Reeves, 2011; Husted and Nickerson, 2014; Schneider and Kunze, 2023). These studies have focused on disaster *declarations*, which is the final result of *both* bureaucrat evaluation *and* politician engagement. To the best of our knowledge, this is the first paper to study whether the biases appear at the earlier, bureaucratic stages, prior to direct politician involvement. Our outcomes of interest (inclusion into PDAs and final receipt of disaster aid) also differ from the majority of the prior literature in that they vary at the county, not state, level; the exception is Schneider and Kunze (2023), which uses county-level observed hurricane exposure as their unit of analysis and examines the resulting county-inclusion in declaration decisions. Our results showing that political bias diminishes in size with flooding intensity is consistent with Schneider and Kunze (2023), which finds similar patterns for hurricanes and their associated wind-speed damages.

Finally, we contribute to the large literature on the economic impacts of natural disasters (Botzen et al., 2019; Boustan et al., 2020). Many such studies rely on measures of damage compiled from historic records, self-reported damages from local weather offices or governments, or FEMA records themselves. Using these as baseline measures of damages creates its own challenges from non-random measurement errors (Gallagher, 2023), as evidenced in our own analysis of the PDA records. By relying on hydrological models using daily estimates of river discharge rates (Harrigan et al., 2020), we construct an external measure of damage to use as a "ground truth" comparison to the PDAs that is less vulnerable to the same social or political influence by which other datasets may be affected. This paper also contributes to the literature by digitizing FEMA's PDA records, a source of administrative data that shows damages as evaluated by FEMA in the immediate aftermath of a disaster.

The remainder of this paper is structured as follows. Section 2 describes the novel administrative dataset and the flooding intensity data derived from hydrological models. Section 3 describes our empirical strategy, presents main results, and discusses potential mechanisms; Section 4 concludes.

2 Institutional Background and Data

2.1 The U.S. Federal Disaster aid process and PDA data

Since FEMA's inception in the 1970s as an agency tasked with emergency management and civil defense, it has been subject to a steady flow of reforms aiming to standardize and professionalize its processes. In particular, the Stafford Act of 1988 established clear protocols for executing emergency management procedures still utilized today. Most importantly, the act gave the executive branch the discretion to declare a federal emergency without congressional approval, leading to disbursal of federal aid for local disaster recovery.

What enables this study to unbundle the decisions of FEMA bureaucrats from those of the president is the three-step administrative process leading up to the declaration of a FEMA disaster. First, the state governor or the tribal leader requests federal aid based on its own initial damage assessment. The request launches the second phase of the federal disaster process, dubbed the preliminary damage assessment (PDA). The PDA aims to "determine the impact and magnitude of damage and the resulting unmet needs of individuals, businesses, the public sector, and the community as a whole (p.3, FEMA, 2025c)," and culminates in a PDA report. The PDAs, taking place shortly after the disaster, are overseen by FEMA bureaucrats. Lastly, the "presidential disaster declaration process" step consists of the state governor or tribal leader applying for federal disaster aid based on the PDA report, followed by the president's ultimate decisions on disaster declarations.[1] Importantly, congressional pressure has led to FEMA publicly releasing the reports from the PDA process since 2008 (Congressional Research Service, 2014), allowing us to observe the FEMA bureaucrats' estimations of the extent of the disasters. Appendix Section A discusses the history of FEMA and its reforms in further detail.

In applying for federal assistance through the PDA process, a governor or tribal leader may request individual assistance (IA), public assistance (PA), or both. IA is made available to individual qualifying households for help in the household disaster recovery, while PA is used by municipalities or local governments for projects such as repairing roads and bridges, removing debris, or rebuilding damaged public buildings. If PA is requested, the PDA report must describe the primary impact of the disaster for which they need assistance as well as an estimate of the public assistance needed to manage these costs. Critically, they additionally list the counties impacted and an estimated countywide per-capita damage impact for each one. The inclusion of counties in these reports and the county-level damage estimates serve as our main variables of interest in this study. Appendix Figure B1 shows an example of the PDA reports, for a flood disaster that occurred in November 2018 in Pennsylvania.

Crucial to the completion of PDAs is the guidance from the FEMA regional office. All states and territories are categorized into one of ten FEMA regions, and each regional office is headed by a Regional Administrator and a Deputy Regional Administrator. During the disaster assessment and declaration process, the regional administrator "has direction, authority, and control over all regional functions and assets (p.27, FEMA, 2025c)." The regional office is additionally tasked with validating the information documented in the PDAs and making a recommendation to FEMA national headquarters and the FEMA administrator regarding whether or not a state should receive a disaster declaration.

The Regional Administrators and Deputy Regional Administrators can be politically appointed, selected by the president but exempt from senate confirmation, or promoted career civil servants (U.S. Congress, 2024). The Regional Offices report to the FEMA Administrator, herself a political appointee who is nominated by the president and appointed under senate confirmation, without a fixed tenure. Importantly, the Regional Office ex-

[1] Two caveats are in order. First, there are cases ("expedited declaration") when the president decides that the PDA and initial damage assessments are not required–hence immediately initiating the presidential disaster declaration process. Second, the state governor has the option to not request for federal aid following the PDA process. Both channels, which could potentially be subject to political bias, are not within the scope of our analysis–in that our data are confined to only disasters that have gone through the PDA process, was not retracted by the governor, and was declared.

ecutive positions are often left unoccupied, with a notable example being the absence of eight out of ten Regional Administrators at the time of Hurricane Katrina's arrival (The White House, 2005). Such variations allow us to investigate the role of political appointees and career civil servants in executive positions of regional offices as a potential mechanism through which political bias can arise.

We compiled and digitized all PDA publications with declared disasters from 2008 onwards into a dataset of 699 presidential disasters with PDAs mentioning flooding or related issues. We further restrict the sample to the 133 disasters that (1) have "flood" as their primary or secondary incident type and (2) had PA requested (so that county-level data are available).[2] We focus on flooding events for two reasons. First, floods are among the most frequently occurring and most damaging natural disasters, causing second largest damage in the U.S. from natural disasters after wind damage (Congressional Budget Office, 2025). Second, the use of hydrological models allows for a standardized and external flooding metric for comparison, an advantage over other natural disasters that are more difficult to measure.

To be clear, the inclusion of counties in a PDA report, or the countywide impact metrics thereof, are not the only avenues of political influence within the bureaucratic federal disaster processes. For example, the president, for certain extreme disasters, can invoke an "expedited declaration" process to skip the first two stages of the disaster process (initial damage assessment and PDA). We leave other points of potential political bias to future research, and focus on biases that occur *within* the PDA process by limiting our sample to disasters with PDAs and with eventual presidential declarations.

2.2 Hydrological model results and flooding intensity

As alluded to above, we capture political bias in FEMA disaster aid by regressing aid outcomes (i.e., inclusion in assistance request and actual receipt of public assistance) against a metric of "flooding intensity" experienced by different counties for each flood disaster. In obtaining such a metric of flooding intensity, we avoid relying on reported damages (from data sets such as SHELDUS, Center for Emergency Management and Homeland Security, 2025), which may be subject to non-random measurement errors

[2]Incidentally, FEMA assigns "flood" as the primary or secondary incident types primarily when they are caused by precipitation (pluvial floods) and overflowing of rivers and streams (fluvial floods). The third type of floods (coastal floods) is mostly observed in disasters classified as "hurricanes" by FEMA. This strengthens the comparability with our hydrological model's results, as the model is driven by gridded estimates of precipitation and riverflow.

(Gallagher, 2023). We also refrain from relying solely on records of local precipitation, as flooding is driven not only by rainfall but also through run-off of rainwater from upstream regions.

Our external flooding intensity metric is instead based on Harrigan et al. (2020), which applies a cutting-edge hydrological model (Van Der Knijff et al., 2010) to a gridded data set of daily precipitation, soil/land-use characteristics, and topographic characteristics to estimate daily river discharge rate (i.e., volume per second of stream flow) at the $0.05° \times 0.05°$ grid level.[3] Verification exercises of Harrigan et al. (2020) data showed that its errors being within 5% to 20% of ground-truth measurements from river observation stations, especially in eastern and western U.S. regions with frequent floods (Copernicus Emergency Management Service, 2024). Data from Harrigan et al. (2020) have been extensively applied to the analysis of historical patterns of riverflow and are used to calibrate multiple flood early-warning systems that are currently operational across the world (Prudhomme et al., 2024).

Figures 1a and 1b present an example of how the Harrigan et al. (2020) daily gridded data are used to derive our flooding intensity metric. After aggregating the daily gridded discharge rate to the census tract level,[4] we use the "incident begin date" and "incident end date" entries from FEMA's Disaster Declarations Summaries (FEMA, 2025a) to obtain the maximum discharge rate observed over the course of the flooding event. Figure 1a shows an example of the maximum daily discharge rate observed for a flooding event in Tennessee, February 2019.[5]

Crucially, we note that the discharge rate *per se* cannot be used as a metric for flooding intensity, as census tracts closer to rivers systematically show larger maximum discharge rate. This is also shown in Figure 1a, where tracts along the Mississippi river (on the western end of Tennessee) and along the Cumberland river (passing through Nashville, point "B") show larger discharge rates than other census tracts.

We thus apply well-known methods in hydrological engineering on "return periods" (Gumbel, 1941; Pappenberger et al., 2012) to the entire historical data of Harrigan et al. (2020) to estimate the discharge rate at different return periods (e.g., 1.5-year, 5-year). The

[3] The original Harrigan et al. (2020) data were produced at $0.1° \times 0.1°$ resolution. We use the most recent version of the data set (GloFas v.4.0), which provide $0.05° \times 0.05°$ discharge rate data.

[4] While within-census tract variation in discharge rate remains minimal, we opt to minimize the aggregation error by weighting each grid by its population density, obtained from Center For International Earth Science Information Network (2016).

[5] FEMA assigns a specific reference number for individual disaster, with separate reference numbers assigned when a disaster (e.g., hurricane) crosses state borders. The FEMA reference number for this event is 4427.

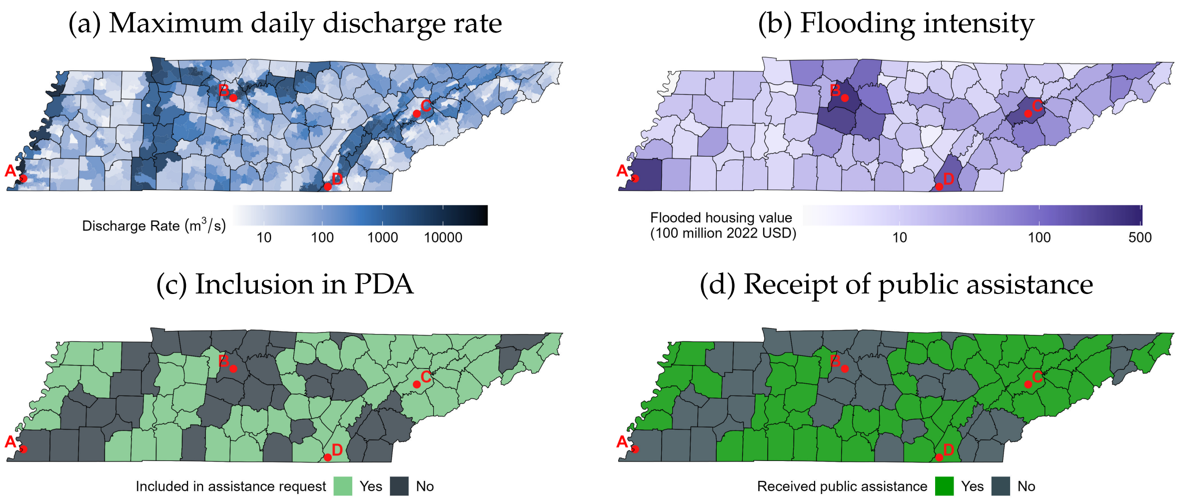

Figure 1. Flooding disaster in Tennessee in February 2019

Notes: Figure illustrates the use of hydrological models in deriving our flooding intensity metric and summarizes the data underlying our outcome variable. (a) presents the maximum daily discharge rate (i.e., volume of streamflow per second) at the census tract level, observed during a flooding event in TN, February 2019. Darker census tracts showed larger streamflow. (b) shows our flooding intensity metric, defined as the sum of housing value in census tracts showing discharge rate larger than that of a 1.5-year flood (see main text). Darker counties experienced stronger flooding damage. (c) shows, in green, counties that were included in FEMA's original public assistance request through the preliminary damage assessment. (d) shows counties that eventually received public assistance in green. Dots A, B, C, D refer to the four major cities of Tennessee, Memphis, Nashville, Knoxville, and Chattanooga, respectively. Discharge rate data from Harrigan et al. (2020) and housing value data from the 2014-2018 5-year American Community Survey.

method establishes, using daily discharge rate from 1979 to 2024, what discharge rate would be considered as a 2-year flood, 5-year flood, and so on at the tract level. A tract's maximum discharge rate exceeding the 5-year return discharge rate, for example, would equate to the census tract experiencing a 5-year *flood*.

We compute our headline flooding intensity metric at the county-disaster level by taking the sum of housing units' values in the census tracts experiencing at least a 1.5-year flood. The housing unit values are obtained from the 5-year American Community Survey (ACS) data in the year prior to the disaster.[6] We test the robustness of our analyses to alternative definitions of flooding intensity, such as using 1.33-year flood or 3-year flood as the cut-off and using census tract population instead of housing value.

Figure 1b shows the result of applying such a method to the February 2019 flood in Tennessee. The results suggest that while all Tennessee counties experienced at least a

[6] For example, for the flood event shown in Figure 1, we use the 2014-2018 5-year ACS data (U.S. Census Bureau, 2024).

1.5-year flood in the event, counties containing major cities (marked with points A, B, C, D, referring to Memphis, Nashville, Knoxville, and Chattanooga, respectively) experienced substantially larger damage than their peers. Such correlation between flooding damage and population density, common in environmental damages (Muller and Mendelsohn, 2009; Hsiang et al., 2019), underlies our use of *within*-county variations in flooding intensity in our empirical analysis. We discuss our identification strategy in greater detail below.

Lastly, the exclusion of certain counties in FEMA's PDA report for the 2019 Tennessee flood provides correlational motivation to our empirical exercise. While Figure 1b suggests that the counties surrounding Memphis and Nashville (A and B) suffered floods similar in intensity to Knoxville and Chattanooga (C and D), Figure 1c shows that only Knoxville and Chattanooga's counties were included in the PDA assistance request. The distribution of counties eventually receiving public assistance (Figure 1d) is almost identical to that of counties included in the initial PDA report (Figure 1c), leading to the final exclusion of Memphis and Nashville's counties from the aid disbursal. County-level vote returns in the 2016 elections show that the majority of Memphis and Nashville's counties voted against the president incumbent as of 2019–versus Knoxville and Chattanooga counties voting largely in favor of the incumbent.

2.3 Additional data

Additional FEMA data. We combine the PDA data with FEMA public records of where and how much PA is granted following disaster declarations. These show how much disaster aid each county received, conditional on their declaration request being approved. Since the PDAs display initial financial assessments and amounts considered to be needed for PA by FEMA bureaucrats, these values can be compared to what was actually disbursed as PA after the declarations have occurred.

For each declared disaster that had the public assistance program approved for use by effected areas, FEMA publishes information on utilized funds as part of their OpenFEMA database (FEMA, 2025b). We use the Public Assistance Funded Project Summaries, which details for each disaster a list of PA applicants and summaries of their corresponding projects funded by federal grant assistance. The projects that fall under the category of PA are those pertaining to publicly owned facilities or qualifying private non-profit organizations that require funding for activities such as protective measures, debris removal, and repairing damages. This data contains the disaster ID, state, and county of the fund allocation as well as the applicant's name, the number of projects the funding is requested for, and the amount of public assistance grant funding available for the applicant to use. We link this PA data with PDA data using the disaster ID.

Career and non-career FEMA executives. For the purposes of assessing the role of career- and non-career leadership, we refer to the de-identified Federal Workforce Data ("FedScope," Office of Personnel Management, 2024). The FedScope data contain the "Terms of Appointment" (TOA) information, which can be used to identify the executive employees and their appointment type (i.e., career versus non-career),[7] and their "work location" can be used to identify the state in which the executives are stationed. Combined, these properties can be used to evaluate whether there were career and/or non-career executives in the FEMA regional offices overseeing the state in which a given disaster took place.[8] The Regional Office executive positions can be filled both by career executives, by non-career executives, a mix of both, or may be entirely vacant.

FedScope data were released on a quarterly basis throughout our sample period. For each disaster, we use the data from the most recent FedScope quarterly release. We also match each disaster-state to the regional office following FEMA's classification (e.g., disasters in New Jersey, New York, Puerto Rico, and Virgin Islands linked with FedScope data of Region II, headquartered in New York).

Vote returns, congressional committees, and time-varying covariates. We utilize several sources of political data. For US presidential election data, we use the "U.S. President 1976–2020" dataset from the MIT Election Data and Science Lab (Data and Lab, 2017). For governor's political party, we use the "United States Governors 1775-2020" dataset from Kaplan (2021). The gubernatorial election results come from CQ Press Voting and Elections Collection (CQ Press, 2025).

For congressional data on committee members, their party affiliations, and their term lengths, we use Grossmann et al. (2024). For FEMA budget data, we rely on monthly reports on the Disaster Relief Fund showing the draw down throughout the year from FEMA's resources (Federal Emergency Management Agency, 2024).

[7] To be precise, we identify TOAs "50-Senior Executive Service - Career," "55-Senior Executive Service - Non-Career," "46-Excepted Service - Executive," "60-Senior Executive Service - Limited Term," and "65-Senior Executive Service - Limited Emergency" TOAs as those belonging to executive positions. FEMA in the sample period did not use Schedule C appointments and "36-Excepted Service - Executive" for its executive positions. The "50" TOA is what we classify as "career" positions.

[8] Strictly speaking, a given executive stationed in a state with a regional office does not have to be posted to a regional office. For example, as of 2024 in California there were three executive positions available, two in the Region IX office in San Francisco (Regional Administrator and Deputy Regional Administrator) and one in the National Incident Management Assistance (West) Team Leader position, in Sacramento. Such cases, however, are very rare and most states with regional offices have 2, 1, or 0 executives at a given point in time–suggesting that the states' executive positions are all occupied by the regional office.

We additionally rely on annual population and median personal income data from Bureau of Economic Analysis (2025), and annual demographic data from Census Bureau (2025). All nominal and monetary data are adjusted to 2022\$ values using annualized Consumer Price Index (CPI).

3 Empirical strategy and results

3.1 Empirical strategy

We capture political bias in FEMA disaster aid by assessing the inclusion of counties in the PDA reports, conditional on flood intensity. Our reduced form equation of interest is

$$y_{1id} = \beta \text{FI}_{id} + \delta \text{MarginPres}_{ie(d)} + \lambda \text{FI}_{id} \text{MarginPres}_{ie(d)} + \alpha_i + \gamma_{s(i),d} + \varepsilon_{id} \tag{1}$$

where y_{1id} is a variable of value = 1 when the county i was included in the PDA report for disaster d. FI_{id} is the flooding intensity for county i and disaster d, defined as the log of sum of housing value affected by a flooding event greater than 1.5-year flood (see Section 2). $\text{MarginPres}_{ie(d)}$ is the vote margin in favor of the incumbent president in county i on the election closest to the occurrence date of disaster d, $e(d)$. $\text{MarginPres}_{ie(d)}$ is in percentages, with positive value representing the majority of county i voting for the incumbent.[9]

δ and λ are the coefficients of interest. $\delta > 0$ would indicate that counties misaligned with the president are less likely to be included in the PDA report. Further, $\lambda < 0$ would translate to the alignment bias *decreasing* in size as the flooding intensity FI_{id} increases.

A distinct threat to the identification of δ and λ, however, is the possibility of FI_{id} being correlated with county-specific characteristics. The example of flood damage in urban and rural counties (Figure 1b) illustrates such a possibility. We explicitly account for this threat by including the county-fixed effect term α_i. The identifying variation thus comes from *within*-county, intertemporal variation in flooding intensity and the variation in counties' inclusion to PDA reports. The identification assumption relies on plausibly random variations in the intensity of flooding events and their timing.

Further, even when we account for county-fixed characteristics *via* α_i, there still is the possibility that certain states are exposed to different temporal trends, or that individual flood disasters possess idiosyncratic properties that are correlated with both their intensity and the PDA's comprehensiveness. The state-by-disaster fixed effect term, $\gamma_{s(i),d}$,

[9] We define "incumbent president" as the president incumbent as of the disaster onset date.

non-parametrically controls for such state-specific trends and disaster characteristics. The equation (1) hence compares intertemporal variation in flood intensity between counties in the *same* state *and* disaster. All error terms are clustered using Conley standard errors with cutoff at 100km, which is the spatial scale of "synoptic" weather systems (pressure, temperature, wind, and water vapor distribution in the upper atmosphere) that drive spatial variations of precipitation and are used as primary input for the gridded precipitation data underlying the hydrological model.

Table 1 presents evidence supporting our empirical strategy. Columns 1 and 2 show the mean and standard deviation of time-varying covariates (e.g., population density) and political variables (e.g., Republican vote share). All variables come from the closest year with relevant data prior to the disaster. Column 3 presents the raw correlation coefficient between our flooding intensity metric FI_{id} and the presented variables, while column 4 shows the same coefficient calculated with the fixed effect terms α_i and $\gamma_{s(i),d}$.

Column 3 results suggest that counties with larger flooding intensity are larger in population density, higher in income, non-white population share, and lower in elderly population share. These counties are also more likely to vote for Democratic presidential candidates and (weakly) less likely to vote in favor of the incumbent president.

Importantly, for all time-varying covariates and for political variables, the fixed effect terms α_i and $\gamma_{s(i),d}$ reduce the magnitude and significance of the correlation coefficients (column 4). Intertemporal variation in flood intensity is not correlated with trends in urbanization (increase in population density), changes in racial demographic characteristics, and income growth. In contrast, increases in flooding intensity are correlated (at a coefficient of −0.017) with decreases in elderly population share. We test the robustness of our results to including these time-varying covariates and their interaction with FI_{id}.

While equation (1) focuses on the inclusion of a county to the PDA report as the outcome variable (Figure 1c), we also assess whether similar patterns of biases are observed at the ultimate receipt of public assistance (Figure 1d). The reduced-form equation is:

$$y_{2id} = \tilde{\beta}\text{FI}_{id} + \tilde{\delta}\text{MarginPres}_{ie(d)} + \tilde{\lambda}\text{FI}_{it}\text{MarginPres}_{ie(d)} + \tilde{\alpha}_i + \tilde{\gamma}_{s(i),d} + \tilde{\varepsilon}_{id} \tag{2}$$

where y_{2id} is a variable of value = 1 when county i eventually receives PA. Note that the right-hand side of equation (2) is identical to that of equation (1). The coefficients of interest are $\tilde{\delta}$ and $\tilde{\lambda}$.

Lastly, the similarity of the spatial distribution of y_{1id} (inclusion of counties in PDA) and y_{2id} (final receipt of PA) leads us to question: how much of the bias, observed in

Table 1. Correlation between flooding intensity FI_{id} and time-varying covariates W_{id}

	Mean	Std. Dev.	$\text{Cor}(\text{FI}_{id}, W_{id})$	$\text{Cor}(\text{FI}_{id}, W_{id} \mid \alpha_i, \gamma_{s(i),d})$
	(1)	(2)	(3)	(4)
A. Time-varying covariates				
Population density (/km^2)	73.509	518.244	0.203***	0.000
			(0.032)	(0.001)
Non-white population share (%)	10.961	12.863	0.122***	-0.001
			(0.028)	(0.004)
Elderly population share (%)	17.975	4.814	-0.366***	-0.017**
			(0.021)	(0.007)
log(Income) (2022$)	10.778	0.243	0.243***	0.003
			(0.028)	(0.009)
B. Political variables				
Democrat vote share (%)	35.075	14.709	0.381***	-0.009
			(0.021)	(0.009)
Republican vote share (%)	61.666	14.750	-0.392***	0.005
			(0.021)	(0.009)
Vote margin in favor of the incumbent president (%)	2.721	39.497	-0.025**	0.009
			(0.01)	(0.025)

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Notes: Table shows correlation coefficient estimates and their significance between flooding intensity FI_{id} and political variables and time-varying covariates. Column 3 shows the raw correlation between the covariates and FI_{id}, while column 4 shows the correlation between the intertemporal variations in FI_{id} and those of the time-varying covariates. All political variables are from the most recent election *before* the disaster. All time-varying covariates are from the year immediately prior to the disaster. Income data adjusted to 2022$ using Consumer Price Index.

(2), is attributable to the bias at the PDA level? We thus conduct a mediation analysis by estimating the following:

$$y_{2id} = \rho y_{1id} + \breve{\beta}\text{FI}_{id} + \breve{\delta}\text{MarginPres}_{ie(d)} + \breve{\lambda}\text{FI}_{it}\text{MarginPres}_{ie(d)} + \breve{\alpha}_i + \breve{\gamma}_{s(i),d} + \breve{\varepsilon}_{id} \qquad (3)$$

where ρ captures the extent to which the original inclusion in the PDA translates to PA receipt. $\breve{\delta}$ and $\breve{\lambda}$ evaluate whether the alignment bias still persists after controlling for the inclusion status of a county *vis à vis* the PDA report. Appendix Figure B2 graphically illustrates the three regressions, (1) to (3).

We carry out several additional analyses to evaluate the validity of our empirical findings in a larger context. First, we verify that it is specifically the alignment with the *president* that drives our findings by substituting the $\text{MarginPres}_{ie(d)}$ term with $\text{MarginGov}_{ie(d)}$, defined as the vote margin in favor of the incumbent *governor* in the closest gubernatorial election.

Second, while our headline results are focused on political bias at the *extensive* margin (i.e., inclusion in PDAs and receipt of PAs), we test whether similar findings hold at the intensive margin by substituting y_{1id} by the "county impact" entry in the PDAs[10] and y_{2id} by the amount of PA eventually received by the county i for flood disaster d.

We then expose our main results to a series of robustness checks. Most importantly, we test whether our coefficient estimates are driven by other time-varying covariates instead of political alignment themselves by adding all covariates in Table 1 and their interactions with FI_{id} to equations (1) to (3). We also account for potential endogeneity in the intertemporal variation of $\text{MarginPres}_{ie(d)}$ by focusing on "battleground counties" and their changes in alignment.

Finally, we investigate potential mechanisms driving this observed political bias within the PDAs and in the disbursal of PA. We estimate the role of mechanisms Z_{id} in driving the δ and λ coefficients using the following specification:

$$\begin{aligned} y_{id} = {} & \beta\text{FI}_{id} + (\delta_0 + \delta_1 Z_{id})\text{MarginPres}_{ie(d)} \\ & + (\lambda_0 + \lambda_1 Z_{id})\text{FI}_{id}\text{MarginPres}_{ie(d)} + \alpha_i + \gamma_{s(i),d} + \varepsilon_{id} \end{aligned} \qquad (4)$$

where y_{id} is either y_{1id} (PDA inclusion of counties) or y_{2id} (final receipt of PA).

Our first mechanism, the existence of career executives in regional FEMA office administrative positions, builds on previous findings on the partisan nature of non-career

[10] In practice, the PDAs have a term for "county impact per capita." We multiply these terms by county population a year prior to the disaster event to obtain the intensive margin counterpart of y_{1id}.

appointments in the federal bureaucracy (Spenkuch et al., 2023) and on the importance of non-political appointments in public sector performance (Aneja and Xu, 2024).

We additionally test whether the balance of disaster relief fund (DRF) at the advent of the disaster changes the significance of political influence. DRF is the congressionally-allocated budget that FEMA has to allocate towards disaster management throughout the year, with each disaster drawing down from this budget. We test whether shortages in the budget has a mitigating effect on politically-biased spending. We also test the the extent to which political bias is driven by a state's congress member in the House of Representatives sitting on the Homeland Security Committee, Transportation and Infrastructure Committee, or the Appropriations Committee. These committees all play a role in the congressional oversight of FEMA. We therefore test whether having a congress member directly involved in FEMA's oversight, and potentially able to provide input into its operations, increases the likelihood of being listed as needing aid or subsequently granted aid.

Lastly, we explore whether the counties' placement in battleground states (defined as states with vote margins within the $[-10\%, 10\%]$ range), the incumbent president's party, and the timing of the disaster coinciding with a presidential election year, explain the δ and λ coefficients.

3.2 Results

3.2.1 Main results: Political bias in disaster aid

Table 2 presents our headline findings. First, column 1 shows the result of simply regressing y_{1id} (dummy variable of county i being included in the PDA for disaster d) against our flood intensity metric, FI_{id}, with county fixed effect α_i. The results suggest that a county's PDA inclusion is indeed tightly linked with flooding intensity. A standard deviation increase in flooding intensity increases the probability of PDA inclusion by 14.5 point (8.96×1.62). Such results confirm that the methods FEMA uses to assess damages following a flood event largely result in accurate reports. The worse the flood is in a given county, the more likely that FEMA's PDA team will indicate that this county is in potential need of federal aid towards public assistance in their report.

Columns 2 and 3 present evidence supporting political bias at the PDA level. Column 2 includes county fixed effect terms to control for time-invariant county characteristics, while column 3 combines both county and disaster-state fixed effects to control for properties

Table 2. Political bias in disaster aid

	Dependent variable:							
	Included in PDA (y_{1id})			Received public assistance (y_{2id})				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FI_{id}	8.96***	9.06***	9.91***	9.58***	9.64***	9.09***	2.30***	0.81
	(1.44)	(1.46)	(1.74)	(1.55)	(1.57)	(1.84)	(0.77)	(0.77)
$\text{MarginPres}_{ie(d)}$		1.21***	0.72**		0.71**	0.93***	−0.27	0.33**
		(0.40)	(0.33)		(0.32)	(0.33)	(0.18)	(0.14)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$		−0.06***	−0.03**		−0.03**	−0.04***	0.01	−0.02**
		(0.02)	(0.02)		(0.02)	(0.02)	(0.01)	(0.01)
$\mathbb{1}[\text{RequestIncluded}]_{id}$							81.04***	83.55***
							(2.30)	(1.97)
County FE	X	X	X	X	X	X	X	X
State-disaster FE			X			X		X
Control for y_{1id}							X	X
N	4539	4539	4539	4539	4539	4539	4539	4539
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.51	0.51	0.60	0.53	0.53	0.60	0.84	0.87

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Table evaluates alignment bias in the inclusion of counties to FEMA's preliminary damage assessment (PDA) report and its effects on eventual receipt of public assistance (PA). Column 1 regresses a dummy variable indicating county i's inclusion for the PDA of disaster d, y_{1id}, against flooding intensity experienced by the county, FI_{id}, with county fixed effects. Columns 2 and 3 estimate political bias by adding $\text{MarginPres}_{ie(d)}$, vote margin in favor of the incumbent president, and its interaction with FI_{id}. The latter has state-disaster fixed effect $\gamma_{s(i)d}$. Columns 4 to 6 repeat columns 1 to 3 for y_{2id}, dummy for eventual public assistance receipt. Columns 7 and 8 have y_{2id} as the outcome variable but controls for the effect of PDA, with column 8 containing $\gamma_{s(i),d}$. All coefficients and standard errors multiplied by 100 for legibility. $\text{MarginPres}_{ie(d)}$ in %.

specific to individual disasters and for state-specific time trends. Both specifications estimate equation (1) by regressing y_{1id} against $\text{MarginPres}_{ie(d)}$, the vote margin of county i for the incumbent president in the previous election closest to flood disaster d, FI_{id}, and their interaction.

We find a statistically significant $\delta > 0$ estimate regardless of the inclusion of the state-disaster fixed effect $\gamma_{s(i)d}$. The point estimates in column 3 suggest that a standard deviation decrease in $\text{MarginPres}_{ie(d)}$ leads to a 4 percentage point drop (-39.497×0.72) in the probability of the county being included in PDA reports for an average intensity flood. Importantly, the negative λ estimates suggest that such biases decline in stronger floods, with the alignment bias eventually becoming insignificant. Such results are consistent with Schneider and Kunze (2023), which finds that marginally-severe disasters are the most susceptible to political influence in the disaster declaration process, while the least severe and most severe hurricanes are largely immune.

Columns 4 to 6 repeat the exercise of columns 1 to 3, but for y_{2id} (i.e., dummy variable of ultimately receiving public assistance). Once again, the receipt of PA is strongly linked with flood intensity, and we find statistically significant $\delta > 0$ and $\lambda < 0$. A standard deviation drop in alignment leads to a 37 point reduction in the probability of receiving public assistance.

Motivated by the resemblance of δ and λ coefficients' sign and significance for equations (1) and (2), columns 7 and 8 evaluate the extent to which the columns 5 and 6 results of bias in PA are driven by the biases "baked in" at the PDA level. The columns add y_{1id} in the right-hand side to the analyses of columns 5 and 6 (equation (3)). The coefficient estimates for y_{1id} imply that a county's PDA inclusion is a major driver of the final receipt of PA, being associated with a 83 percentage point increase in PA receipt probability. Nevertheless, the δ and λ coefficients for column 8 suggests that even after controlling for PDA inclusion, one standard-deviation misaligned counties are 13 percentage points less likely to receive disaster aid compared to counties within the same state–suggesting that there is additional political bias introduced even at the second, politician-driven stage.

Taken together, this indicates that the bureaucratic stage of this process is not immune to political bias. Bureaucrats are more likely to flag a county as needing public assistance if it is politically aligned with the incumbent president, even before the direct involvement of the executive branch comes into play, indicating pre-compliance behavior with the party in power not previously documented. Much of this bias is later reflected in the final outcome of the disaster aid process, but exacerbated when the executive branch itself provides input. Only the most extreme flooding events appear politically unbiased in their assessments at both the bureaucrat stage and aid allocation stage.

3.2.2 Additional results

Our finding of political biases are not confined to the decisions at the extensive margin (i.e., inclusion of counties in PDAs and their final receipt of aid). Appendix Table B1 replicates the Table 2 analysis, but for the intensive margins of the disaster aid process. Columns 1 to 3 take as outcome variable the log of "county impact" values in the PDA reports, which reflect the FEMA PDA team's evaluation of the assistance needed for damage restoration. Columns 4 to 6 use the log of PA eventually disbursed as the outcome variable. The results are consistent with Table 2, with reductions in county impact values and in final PA disbursed in misaligned counties, and the bias diminishing with FI_{id}.

Further, Appendix Table B2 presents indirect evidence suggesting that it is indeed the alignment with the incumbent president that decides our results, by substituting the $\mathrm{MarginPres}_{ie(d)}$ variables by vote margin in favor of the incumbent governor in the most recent election ($\mathrm{MarginGov}_{id}$). We fail to find any statistically significant effects of gubernatorial alignment. Appendix Table B3 illustrates that that such absence also stands at the intensive margin.

Appendix Table B4 strengthens our identification for our $\mathrm{MarginPres}_{ie(d)}$ variable by subsetting our sample to "battleground" counties, defined as the counties whose vote margins in the election were within the $[-10\%, 10\%]$ range. The identification assumption for $\mathrm{MarginPres}_{ie(d)}$ relies on the plausibly exogenous variation in vote margins in counties with close elections. The δ and λ coefficient estimates are once again consistent with Table 2. Columns 2 and 3 imply that the same results follow when we substitute $\mathrm{MarginPres}_{ie(d)}$ with a dummy of alignment with the president, *à la* Lee (2008).

Lastly, the use of log-transformation in the definition of FI_{id} means that counties without any flooded census tracts (and hence has $\mathrm{FI}_{id} = 0$) are dropped from the regressions in Table 2. Appendix Table B5 evaluates whether there are biases in treating the counties that have been flooded versus not flooded. The table's regressions include all flooded and unflooded counties in the sample, use a redefined flooding intensity metric,[11], and include a dummy variable of "at least one census tract flooded" ($\mathrm{Flooded}_{id}$). The interac-

[11] To be precise, we define the new metric $\widetilde{\mathrm{FI}}_{id}$ as

$$\widetilde{\mathrm{FI}}_{id} := \begin{cases} \mathrm{FI}_{id} \text{ if } \mathrm{FI}_{id} > 0 \\ 0 \text{ if } \mathrm{FI}_{id} = 0 \end{cases}$$

tion term $\text{Flooded}_{id}\text{MarginPres}_{ie(d)}$ implies that flooded counties are 25 percentage points less likely to be included in the PDA if they are one SD misaligned with the incumbent (-39.497×0.63). The results for other variables are similar to Table 2, with misaligned counties being less likely to be included in PDAs and such biases diminishing with flood intensity.

3.2.3 Mechanisms

What are the potential drivers of the δ and λ estimates? We rely on the administrative process surrounding FEMA disaster aid (Section 2) to explore the role of career and non-career executives in FEMA regional offices. Column 1 of Table 3 shows the estimates of equation (4), with the $\mathbb{1}[\text{CareerExec}]_{r(i),d}$ a variable of value = 1 when there is a career civil servant in the role of executive in the FEMA regional office that oversees the county i, at the advent of the flood disaster.[12] This occurs for 65% of all county-disaster observations in the sample.

The coefficient estimates suggest that the δ and λ coefficients are significantly smaller in size when there is a career executive in the regional office overseeing the disaster, compared to cases in which a regional office lacks an executive manager or is managed by a non-career political appointee. This is consistent with the career executives being apolitical and not necessarily politically aligned with the executive politician (Spenkuch et al., 2023) and hence reducing political bias, improving public sector performance (*à la* Aneja and Xu, 2024).

Column 2 of Table 3 explores the role of non-career executives, by adding dummy variables of non-career executives' existence to the right-hand side, $\mathbb{1}[\text{NonCareerExec}]_{r(i),d}$ (true for 52% of observations). Whereas the coefficients on $\mathbb{1}[\text{CareerExec}]_{r(i),d}$ demonstrate that bias reduces under the oversight of a career executive, the coefficients on the new dummy variable, $\mathbb{1}[\text{NonCareerExec}]_{r(i),d}$, are statistically insignificant. This suggests that the presence (or absence) of a political appointee fails to mitigate any political bias in the assessment process.

Column 3 uses an alternative dummy variable of "FEMA career executive exists in the state of county i" (who are very likely not stationed in the regional office) and finds no significant heterogeneity in δ and λ terms. This indirectly suggests that it is career

[12] To be clear, the dummy variable describes the existence of a career executive in the state in which the regional office is placed, which we equate to "being in regional office" as it is very rare that the executive is not stationed at the regional office. See footnote 8.

Table 3. Mechanism: Career executives in FEMA regional offices

	Dependent variable:					
	Included in PDA (y_{1id})			Received public assistance (y_{2id})		
	(1)	(2)	(3)	(4)	(5)	(6)
FI_{id}	9.26^{***}	8.87^{***}	9.37^{***}	9.49^{***}	8.59^{***}	8.36^{***}
	(1.86)	(2.24)	(1.89)	(2.07)	(2.42)	(2.00)
$\text{MarginPres}_{ie(d)}$	1.99^{***}	2.06^{***}	0.88^{**}	1.22^{*}	0.30	0.89^{**}
	(0.64)	(0.69)	(0.43)	(0.64)	(0.72)	(0.41)
$\text{MarginPres}_{ie(d)}\mathbb{1}[\text{CareerExec}]_{r(i),d}$	-1.67^{**}	-1.63^{**}		-0.42	0.30	
	(0.78)	(0.82)		(0.78)	(0.84)	
$\text{MarginPres}_{ie(d)}\mathbb{1}[\text{NonCareerExec}]_{r(i),d}$		-0.11			1.11^{*}	
		(0.63)			(0.67)	
$\text{MarginPres}_{ie(d)}\mathbb{1}[\text{CareerExecState}]_{s(i),d}$			-0.49			0.11
			(1.56)			(1.46)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	-0.09^{***}	-0.10^{***}	-0.04^{*}	-0.06^{*}	-0.01	-0.04^{**}
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\mathbb{1}[\text{CareerExec}]_{r(i),d}$	0.08^{**}	0.08^{*}		0.02	-0.02	
	(0.04)	(0.04)		(0.04)	(0.04)	
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\mathbb{1}[\text{NonCareerExec}]_{r(i),d}$		0.00			-0.06^{*}	
		(0.03)			(0.03)	
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\mathbb{1}[\text{CareerExecState}]_{s(i),d}$			0.02			-0.01
			(0.06)			(0.06)
County & state-disaster FE	X	X	X	X	X	X
N	4539	4539	4539	4539	4539	4539
R^2	0.60	0.60	0.60	0.60	0.60	0.60

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Table explores potential drivers of the political bias in disaster aid. Columns 1 and 2 evaluate the role of career and non-career executives in FEMA regional offices in political bias at the bureaucrat-driven PDA stage. Column 3 studies the role of career executives in the state of disaster occurrence. Columns 4 and 6 repeat the exercise but for eventual receipt of disaster aid (final decision after presidential intervention). Conley standard errors, with 100km cutoff, shown in parentheses. Point estimates and standard error multiplied by 100 for legibility.

executives stationed specifically in FEMA regional offices who dampen the political bias.

Columns 4 to 6 of Table 3 repeat columns 1 to 3 but for the final receipt of public assistance, after the president has intervened. Interestingly, the existence of career executives no longer reduces the δ and λ after the presidential engagement. This implies that the political intervention *reverses* the bias-removing effect of the career executive. Columns 7 and 8 of Appendix Table B6 present empirical evidence that supports this hypothesis. The table also illustrates that our results are robust to using a more parsimonious specification, versus the fully specified model used in Table 3, which include all possible combinations of the dummy variables, FI_{id}, and $\text{MarginPres}_{ie(d)}$.

The importance of regional office executives in the δ and λ, combined with the partisan nature of the non-career executives' appointment, raises the possibility that the executive politician *responds* differently when receiving the PDA from a career bureaucrat, versus a politically-appointed executive. To test this, we regress the dummy of eventual aid receipt (y_{2id}) against the county's inclusion to the PDA (y_{1id}) and its interaction with the existence of career- and non-career executives ($\mathbb{1}[\text{CareerExec}]_{r(i),d}$ and $\mathbb{1}[\text{NonCareerExec}]_{r(i),d}$) in in the regional offices. As presented in Appendix Table B7, we fail to find evidence of changes in eventual aid dissemination decisions in response to career executive versus non-career executive-led PDAs. We take this as further indication of bias being driven by the pre-compliance of political appointees, rather than the executive branch responding more favorably to reports coming from these appointees.

Contrary to the effect of regional FEMA office leadership, we fail to find evidence suggesting that the remaining balance of the disaster relief fund (DRF) at the time of the disaster matters in deciding δ and λ. The results, shown in Appendix Table B8, are consistent with DRF being adjustable with supplemental appropriations in cases of emergency–thus not being perceived as a stringent source of "binding constraint" that disciplines political bias.

Further, building on our preceding analysis involving close elections (Appendix Table B4), we assess whether the "battleground" status of a county in the most recent election explains the heterogeneity in δ and λ coefficients. The coefficient estimates, presented in Appendix Table B9, fail to find evidence suggesting such associations, for both the battleground status of the county and its state. We also do not find heterogeneity from the party of the incumbent president (Democrat versus Republican) and across presidential administrations (Appendix Table B10). These suggest that the alignment biases are not specific to certain counties, states, and administrations.

We do find evidence, however, suggesting that political bias in the PA *controlling* for PDA request ($\check{\delta}$, $\check{\lambda}$ in equation (3)) are larger in size for disasters occurring in election years (column 3 of Appendix Table B9). This indirectly implies that the incumbent president is more likely to intervene and bias the aid disbursal in favor of the aligned counties for election-year disasters.

We also rule out the importance of the House of Representative's oversight using the state's representative being a member of either the Homeland Security Committee, Transportation and Infrastructure Committee, or the Appropriations Committee. We do not find significant effects from such regressions, which is consistent with the PDAs taking place soon after the disaster aid process, which limits the window of opportunity for Congressional intervention (Appendix Table B11).

We further evaluate whether fluctuations in the staffing levels of FEMA could explain the heterogeneity in political bias. We do not find significant effects from changes in total number of FEMA full-time employees, either including or excluding non-career appointments (Appendix Table B12). This suggests that changes in FEMA's capacity are not likely what is driving the δ and λ coefficients.

Finally, we shed light on the *components* of the disaster aid that drives the political bias by estimating equation (2) for the log of PA disbursed for different types of recovery activities. The results, shown in Appendix Table B13, suggest that it is primarily expenditures on items with significant discretion (e.g., recovery efforts for "Protective measures" and "Recreational or other" infrastructures) that show significant δ and λ coefficients. In contrast, we fail to find statistically significant δ and λ in the PA for "Debris removal" and "Public buildings."

3.2.4 Robustness checks

Crucial to our interpretations of δ and λ as estimates of political bias is the assumption that such coefficients are not explained by intertemporal variations in time-varying county characteristics. While quasi-experimental variations in flooding intensity and their randomness in timing arguably confer credence to such assumptions, Table 4 empirically tests the violation of such assumptions by using observable time-varying characteristics. While we only show the estimates of δ and λ for legibility, Appendix Table B14 shows the full list of coefficients estimates and their standard errors.

Column 2 adds time-varying characteristics W_{id} shown in Table 1 (population density, non-white population share, elderly population share, and log of income) to the right-

Table 4. Robustness check: Clustering levels and time-varying covariates

	Dependent variable:					
	Included in assistance requests			Received public assistance		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{MarginPres}_{ie(d)}$	0.72***	0.82**	0.82**	0.93***	1.02***	1.04***
	(0.23)	(0.34)	(0.33)	(0.25)	(0.33)	(0.33)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	−0.03***	−0.04**	−0.04**	−0.04***	−0.05***	−0.05***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
County & State-disaster FE	X	X	X	X	X	X
W_{id} included		X	X		X	X
$W_{id}\text{FI}_{it}$ included			X			X
Alternative SE clustering	X			X		
N	4539	4539	4539	4539	4539	4539
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.60	0.60	0.60	0.60	0.60	0.60

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Table shows the robustness of our headline results. Columns 1 and 4 allow correlation of errors across county and time by clustering the standard errors at the state level, while columns 2 and 5 add time-varying covariates, shown in Table 1, to the equation Columns 3 and 6 also add the interaction between time-varying covariates and the flooding intensity FI_{id}. See Appendix Table B14 for coefficient estimates not shown in the table.

hand side of equation (1). The significance of δ does not change and if anything, increases in its magnitude. Column 3 then interacts the W_{id} with FI_{id}, and find that the λ coefficients' significance do not change either. Columns 5 and 6 repeat the estimation for y_{2id} (dummy variable of PA receipt) and find the same robustness.

Such results suggest that indeed, the δ and λ coefficients are not likely driven by intertemporal variations in observable characteristics. For the δ and λ to be asymptotically biased, there must be an unobserved county-level time-varying covariates that are not captured by the state-time fixed effect and are not correlated with population density, demographic characteristics, and income growth. This is arguably not very plausible.

Another potential threat to our finding is that the significance of δ and λ coefficients are affected by our choice of Conley standard errors. Columns 1 and 4 in Table 4 relax this by clustering at the state level, hence allowing errors to be correlated over county and over observation years. This does not change our results.

As discussed in Section 2, the definition of FI_{id} requires a "cutoff point" in the return period of floods for a census tract to be considered "flooded." While we use 1.5-year flood for our headline results, Appendix Tables B15 and B16 imply that the significance δ and λ are robust to definitions of FI_{id} using 1.25-year, 1.33-year, 2-year, and 3-year floods (columns 1 to 5). Interestingly, we see that the δ and λ coefficients lose significance starting from when we use more stringent thresholds (i.e., including only census tracts that experienced stronger than 4-year and 5-year floods), which is consistent with the $\lambda < 0$ estimate suggesting that political bias disappears for the strongest floods. This suggests that the political biases are no longer relevant for floods stronger than 4-year floods. Column 8 of Appendix Table B16 suggests that the results are also robust to using population of census tracts, instead of housing value, while the λ loses its significance for y_{1id} (inclusion in PDA), in Appendix Table B15.

4 Conclusion

Through the use of novel county-level FEMA administrative data and flood damage assessments derived from hydrological models, we demonstrate that bureaucratic elements of the federal disaster aid allocation process exhibit political bias in support of the incumbent president. Initial preliminary damage assessments conducted by FEMA bureaucrats in support of informing a disaster declaration decision are more likely to include counties that align politically with the presidential party in office, an indication of pre-compliance behavior. This bias has significant implications. In particular, a single standard deviation decrease in that county's alignment with the president decreases their likelihood of being assessed for federal aid by 4% if they face an average-sized flood. As the average amount of public aid disbursal a county receives following a declaration is \$1.3 million, these assessments carry high stakes. These political biases are most important when disasters result in relatively low amounts of flood damages and decline with disaster severity, eventually becoming insignificant. Subsequent biases in public aid disbursal are partially explained by the underlying biases from these preliminary damage assessments, since the receipt of aid in the first place is highly linked to a county's inclusion in a PDA. However, further bias enters at the aid distribution decision stage, following the direct involvement of the executive branch.

We identify a driver of this bias as the prevalence of political appointees serving as FEMA regional office executives compared to career, non-political bureaucrats. Disasters occurring in times when there are career civil servants serving as executives of the regional office in which the disaster takes place exhibit less political bias in the assessment process. The lack of political bias in the bureaucratic stage in these cases is later reversed following the involvement of the executive branch at the aid distribution stage. On the other hand, disasters taking place within regions overseen by non-career executives display evidence of pre-compliance with the political alignment of the executive branch.

We rule out the possibility that the amount of money remaining in FEMA's disaster relief fund plays a role in disciplining the prevalence of political bias. Similarly, we establish that political alignment between an impacted county and its House representatives sitting on FEMA oversight committees does not impact our results. This further supports the consensus that the political bias we observe here arises in the early stages of the disaster assessment process, prior to any potential involvement by Congress.

These results shed light on the relationship between political and bureaucratic entities in their joint efforts to manage resource allocation within the government. We present how the bureaucrat-driven, standardized processes of disaster assessment, meant to be apolitical, is nevertheless vulnerable to political influence. Particularly at times when political appointees hold executive positions within agencies, those within the agency pre-comply with the political preferences of the executive branch.

As such, this setting underscores the tension that exists within federal agencies staffed by career civil servants, but overseen by political appointees, and the different incentives these two groups may face, with career civil servants seemingly mitigating political influence when in positions of leadership. This very tension subsequently has consequences for eventual behavior of governing bodies and allocation of resources.

With the increasing frequency of disasters requiring federal emergency declarations and assistance, these results provide several insights for policymakers interested in navigating these catastrophes in an equitable manner. While assessments and aid disbursal follow flood severity, particularly for the most damaging events, less damaging storms demonstrate susceptibility to political bias. This calls attention to the potential need for more standardization in assessment processes and more oversight of political appointees.

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Appendix

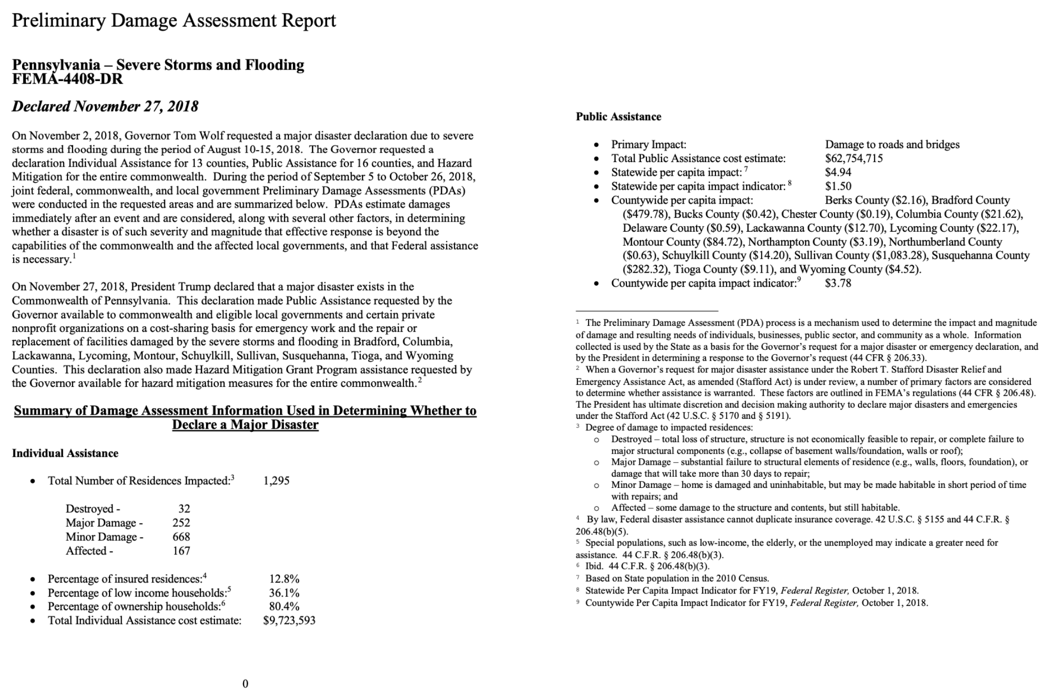
A History of FEMA reforms and the appointment of its executives

Since FEMA's inception in the 1970s as an agency tasked with emergency management and civil defense, it has been subject to a steady flow of reforms aiming to standardize and professionalize its processes. Precedent for the federal government stepping in in an emergency situation dates back to the early 1800s (fema), but it was largely handled in an ad-hoc fashion, with several different federal agencies in charge of coordinating relief efforts to the effect of poor results overall. In an attempt to increase the efficiency of disaster responses and consolidate control in these events, President Carter signed an executive order in 1979 establishing FEMA as an agency. Soon after, the Stafford Act of 1988 established clear protocols for executing emergency management procedures still utilized today. Most importantly, the act gave the executive branch the discretion to declare a federal emergency without congressional approval–leading to disbursal of federal aid for local disaster recovery.

Dating back to its establishment, it has likewise been common practice to have a political appointees heading the agency and managing the 10 regional offices, although this system has long been a source of criticism. FEMA was known colloquially during the 80s and 90s as a largely inefficient and incompetent government agency, with US Senator Fritz Hollings referring to it as 'the sorriest bunch of bureaucratic jackasses I've ever known' after its disastrous handling of a 1988 hurricane in South Carolina (time). President Clinton, in an effort to increase the efficacy of the organization added FEMA to his Cabinet, but this progress was largely negated following the September 11th terrorist attacks, when FEMA was subsumed by the newly created Department of Homeland Security. As national efforts were focused on war and anti-terrorism efforts, FEMA saw massive cuts in funding and the departure of many employees. It again fell into the spotlight, however, after its poor handling of Hurricane Katrina. In particular, it was seen as a failure that at the time of the catastrophe, eight out of ten regional office administrator positions were filled by those working in acting capacities, stretching the capabilities of the agency (The White House, 2005). This public failure spurred the passage of the 2006 Emergency Management Reform Act which formed FEMA again into a distinct federal agency, housed in the DHS.

Several other reforms of the Stafford Act have been passed following major events, although the challenge of maintaining political appointees capable of handling large-scale disasters remains. Very frequently, bureaucrats operate as administrators in acting capacities while nominations and confirmations of political appointees progress slowly. This distinction, and the resulting fluctuation in the number of political appointees throughout FEMA at any given time, allows for our analysis of the influence of political appointees on the disaster assessment and declaration process.

B Additional Tables and Figures



Preliminary Damage Assessment Report

Pennsylvania – Severe Storms and Flooding
FEMA-4408-DR

Declared November 27, 2018

On November 2, 2018, Governor Tom Wolf requested a major disaster declaration due to severe storms and flooding during the period of August 10-15, 2018. The Governor requested a declaration Individual Assistance for 13 counties, Public Assistance for 16 counties, and Hazard Mitigation for the entire commonwealth. During the period of September 5 to October 26, 2018, joint federal, commonwealth, and local government Preliminary Damage Assessments (PDAs) were conducted in the requested areas and are summarized below. PDAs estimate damages immediately after an event and are considered, along with several other factors, in determining whether a disaster is of such severity and magnitude that effective response is beyond the capabilities of the commonwealth and the affected local governments, and that Federal assistance is necessary.[1]

On November 27, 2018, President Trump declared that a major disaster exists in the Commonwealth of Pennsylvania. This declaration made Public Assistance requested by the Governor available to commonwealth and eligible local governments and certain private nonprofit organizations on a cost-sharing basis for emergency work and the repair or replacement of facilities damaged by the severe storms and flooding in Bradford, Columbia, Lackawanna, Lycoming, Montour, Schuylkill, Sullivan, Susquehanna, Tioga, and Wyoming Counties. This declaration also made Hazard Mitigation Grant Program assistance requested by the Governor available for hazard mitigation measures for the entire commonwealth.[2]

Summary of Damage Assessment Information Used in Determining Whether to Declare a Major Disaster

Individual Assistance

- Total Number of Residences Impacted:[3] 1,295

  Destroyed - 32
  Major Damage - 252
  Minor Damage - 668
  Affected - 167

- Percentage of insured residences:[4] 12.8%
- Percentage of low income households:[5] 36.1%
- Percentage of ownership households:[6] 80.4%
- Total Individual Assistance cost estimate: $9,723,593

0

Public Assistance

- Primary Impact: Damage to roads and bridges
- Total Public Assistance cost estimate: $62,754,715
- Statewide per capita impact:[7] $4.94
- Statewide per capita impact indicator:[8] $1.50
- Countywide per capita impact: Berks County ($2.16), Bradford County ($479.78), Bucks County ($0.42), Chester County ($0.19), Columbia County ($21.62), Delaware County ($0.59), Lackawanna County ($12.70), Lycoming County ($22.17), Montour County ($84.72), Northampton County ($3.19), Northumberland County ($0.63), Schuylkill County ($14.20), Sullivan County ($1,083.28), Susquehanna County ($282.32), Tioga County ($9.11), and Wyoming County ($4.52).
- Countywide per capita impact indicator:[9] $3.78

[1] The Preliminary Damage Assessment (PDA) process is a mechanism used to determine the impact and magnitude of damage and resulting needs of individuals, businesses, public sector, and community as a whole. Information collected is used by the State as a basis for the Governor's request for a major disaster or emergency declaration, and by the President in determining a response to the Governor's request (44 CFR § 206.33).

[2] When a Governor's request for major disaster assistance under the Robert T. Stafford Disaster Relief and Emergency Assistance Act, as amended (Stafford Act) is under review, a number of primary factors are considered to determine whether assistance is warranted. These factors are outlined in FEMA's regulations (44 CFR § 206.48). The President has ultimate discretion and decision making authority to declare major disasters and emergencies under the Stafford Act (42 U.S.C. § 5170 and § 5191).

[3] Degree of damage to impacted residences:
- Destroyed – total loss of structure, structure is not economically feasible to repair, or complete failure to major structural components (e.g., collapse of basement walls/foundation, walls or roof);
- Major Damage – substantial failure to structural elements of residence (e.g., walls, floors, foundation), or damage that will take more than 30 days to repair;
- Minor Damage – home is damaged and uninhabitable, but may be made habitable in short period of time with repairs; and
- Affected – some damage to the structure and contents, but still habitable.

[4] By law, Federal disaster assistance cannot duplicate insurance coverage. 42 U.S.C. § 5155 and 44 C.F.R. § 206.48(b)(5).

[5] Special populations, such as low-income, the elderly, or the unemployed may indicate a greater need for assistance. 44 C.F.R. § 206.48(b)(3).

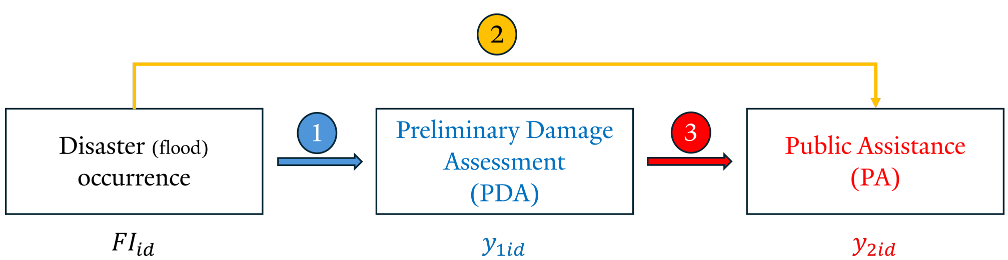
[6] Ibid. 44 C.F.R. § 206.48(b)(3).

[7] Based on State population in the 2010 Census.

[8] Statewide Per Capita Impact Indicator for FY19, *Federal Register,* October 1, 2018.

[9] Countywide Per Capita Impact Indicator for FY19, *Federal Register,* October 1, 2018.

Appendix Figure B1. Example of a preliminary damage assessment (PDA) report



Appendix Figure B2. Illustration of reduced-form equations of interest

Appendix Table B1. Political bias in disaster aid (intensive), from alignment with the incumbent president

	Dependent variable:							
	log(AssistanceRequested)			log(AssistanceReceived)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FI_{id}	5.60	4.03	5.74	−1.95	−0.59	24.68	−1.30	15.65
	(9.37)	(9.27)	(15.00)	(12.64)	(10.99)	(16.19)	(10.91)	(15.18)
$MarginPres_{ie(d)}$		4.54***	5.07**		10.28***	6.60***	−0.08	0.47
		(1.65)	(2.47)		(3.16)	(2.15)	(2.77)	(1.74)
$FI_{id}MarginPres_{ie(d)}$		−0.21***	−0.24**		−0.51***	−0.33***	0.00	−0.03
		(0.08)	(0.12)		(0.16)	(0.11)	(0.14)	(0.09)
$\mathbb{1}[RequestIncluded]_{id}$							73.46***	51.25***
							(6.00)	(5.03)
County FE	X	X	X	X	X	X	X	X
State-disaster FE			X			X		X
Control for request							X	X
N	1426	1426	1426	1534	1534	1534	1335	1335
Dep. var.: Mean	13.13	13.13	13.13	12.91	12.91	12.91	12.91	12.91
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.82	0.82	0.88	0.69	0.71	0.84	0.86	0.92

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Table repeats the exercise of 2, but for biases at the intensive margin. The y_{1id} and y_{2id} variables are now the log of "PA requested" in the PDA and actual PA received, respectively. All outcomes transformed to 2022$ using Consumer Price Index.

Appendix Table B2. Political bias in disaster aid (extensive), from alignment with the incumbent governor

	Dependent variable:							
	Included in assistance requests			Received public assistance				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FI_{id}	8.96***	8.43***	9.49***	9.58***	9.29***	8.54***	2.48***	0.62
	(1.44)	(1.58)	(1.78)	(1.55)	(1.53)	(1.83)	(0.84)	(0.88)
$\mathrm{MarginGov}_{ie}$		−0.67	−0.54		−0.34	−0.64	0.20	−0.19
		(0.61)	(0.54)		(0.59)	(0.58)	(0.56)	(0.48)
$\mathrm{FI}_{id}\mathrm{MarginGov}_{ie}$		0.04	0.03		0.02	0.03	−0.01	0.01
		(0.03)	(0.03)		(0.03)	(0.03)	(0.03)	(0.02)
$\mathbb{1}[\mathrm{RequestIncluded}]_{id}$							80.71***	83.55***
							(2.30)	(1.97)
County FE	X	X	X	X	X	X	X	X
State-disaster FE			X			X		X
Control for request							X	X
N	4539	4519	4519	4539	4519	4519	4519	4519
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.51	0.51	0.60	0.53	0.53	0.59	0.84	0.87

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Notes: Table repeats the exercise of Table B10, but for $\mathrm{MarginGov}_{ie}$, which is the vote margin in favor of the incumbent governor in the most recent gubernatorial election.

Appendix Table B3. Political bias in disaster aid (intensive), from alignment with the incumbent governor

	Dependent variable:							
	log(AssistanceRequested)			log(AssistanceReceived)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FI_{id}	5.60	1.39	−2.67	−1.95	−3.95	26.13	0.42	15.44
	(9.37)	(9.98)	(15.88)	(12.64)	(13.28)	(16.68)	(11.38)	(15.75)
$MarginGov_{ie}$		−6.74	-10.25^{*}		−4.30	−4.88	1.13	−1.74
		(6.73)	(5.61)		(5.95)	(4.71)	(2.64)	(3.97)
$FI_{id}MarginGov_{ie}$		0.35	0.51^{*}		0.22	0.20	−0.04	0.07
		(0.33)	(0.27)		(0.30)	(0.23)	(0.13)	(0.19)
$\mathbb{1}[RequestIncluded]_{id}$							73.14^{***}	51.09^{***}
							(5.87)	(5.00)
County FE	X	X	X	X	X	X	X	X
Election FE	X	X	X	X	X	X	X	X
State-disaster FE			X			X		X
Control for request							X	X
N	1635	1635	1635	1780	1780	1780	1530	1530
Dep. var.: Mean	13.16	13.16	13.16	12.96	12.96	12.96	12.96	12.96
FI_{it}: Mean	20.67	20.67	20.67	20.67	20.67	20.67	20.67	20.67
FI_{it}: SD	1.63	1.63	1.63	1.63	1.63	1.63	1.63	1.63
R^2	0.82	0.82	0.85	0.72	0.74	0.80	0.86	0.90

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Notes: Table repeates Appendix Table B2, but for biases at the intensive margin (log of assistance requested in the PDA and in the actual amount of PA disbursed).

Appendix Table B4. Additional analysis: Variations in alignment within battleground counties

	Dependent variable:					
	Included in assistance requests			Received public assistance		
	(1)	(2)	(3)	(4)	(5)	(6)
FI_{id}	13.76***	17.16***	11.04***	12.13***	17.55***	10.58***
	(3.11)	(3.99)	(1.93)	(4.51)	(5.08)	(2.18)
$MarginPres_{ie(d)}$	10.67*			15.87***		
	(5.93)			(6.06)		
$AlignedPres_{ie(d)}$		123.38*	46.12*		205.70***	61.80**
		(70.90)	(27.53)		(77.86)	(31.24)
$FI_{id}MarginPres_{ie(d)}$	−0.54**			−0.75***		
	(0.27)			(0.27)		
$FI_{id}AlignedPres_{ie(d)}$		−6.29*	−2.19*		−9.84***	−2.94**
		(3.34)	(1.28)		(3.56)	(1.47)
County & State-disaster FE	X	X	X	X	X	X
Sample	Battleground	Battleground	Full	Battleground	Battleground	Full
N	815	815	4539	815	815	4539
Dep. var.: Mean	0.21	0.21	0.22	0.23	0.23	0.22
FI_{id}: Mean	21.11	21.11	20.70	21.11	21.11	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.70	0.70	0.60	0.69	0.69	0.60

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Table tests the existence of political bias in battleground counties, defined as counties that had a vote margin within ± 10% in the most recent presidential election (preceding each disaster). Columns 1 and 4 use the same specification as Table 2 column 2, while columns 2, 3, 5, and 6 use the dummy variable of the vote margin being positively in favor of the incumbent president. Columns 2 and 5 hence use quasi-experimental variations in county alignment for battleground counties.

Appendix Table B5. Additional analysis: Flood occurrence, flood intensity, and political bias

	Dependent variable:					
	Included in assistance requests			Received public assistance		
	(1)	(2)	(3)	(4)	(5)	(6)
Flooded_{id}	18.57***	−39.86**	−38.88**	−32.98*	−33.23*	−1.87
	(2.38)	(16.93)	(18.38)	(18.87)	(19.32)	(9.00)
$\widetilde{\text{FI}}_{id}$		2.85***	2.94***	2.72***	2.69***	0.31
		(0.81)	(0.90)	(0.90)	(0.94)	(0.43)
$\text{MarginPres}_{ie(d)}$			0.07*		0.08**	0.03
			(0.03)		(0.03)	(0.02)
$\text{Flooded}_{id}\text{MarginPres}_{ie(d)}$			0.63**		0.76***	0.25**
			(0.27)		(0.27)	(0.12)
$\widetilde{\text{FI}}_{id}\text{MarginPres}_{ie(d)}$			−0.03**		−0.04***	−0.01**
			(0.01)		(0.01)	(0.01)
$\mathbb{1}[\text{RequestIncluded}]_{id}$						80.65***
						(2.13)
County FE	X	X	X	X	X	X
State-disaster FE	X	X	X	X	X	X
Control for request						X
N	8453	8453	8453	8453	8453	8453
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.39	0.39	0.48	0.42	0.49	0.82

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Notes: Table tests the existence of political bias for the *full* sample, rather than dropping counties that did not have any census tracts that experienced a 1.5-year flood damage. The $\widetilde{\text{FI}}_{id}$ is defined as FI_{id} if $\text{FI}_{id} > 0$, 0 otherwise, and Flooded_{id} is a dummy variable of FI_{id} being strictly positive.

Appendix Table B6. Mechanisms: Regional office leadership by executives, including equation (3) regression

	Dependent variable:					
	Included in assistance requests		Received public assistance			
	(1)	(2)	(3)	(4)	(5)	(6)
FI_{id}	9.79^{***}	9.26^{***}	9.06^{***}	9.49^{***}	0.87	1.75^{*}
	(1.72)	(1.86)	(1.85)	(2.07)	(0.78)	(0.95)
$\text{MarginPres}_{ie(d)}$	1.95^{***}	1.99^{***}	1.26^{**}	1.22^{*}	−0.38	−0.44
	(0.64)	(0.64)	(0.63)	(0.64)	(0.38)	(0.39)
$\text{MarginPres}_{ie(d)}\mathbb{1}[\text{CareerExecutive}]_{id}$	-1.66^{**}	-1.67^{**}	−0.43	−0.42	0.96^{**}	0.97^{**}
	(0.79)	(0.78)	(0.78)	(0.78)	(0.48)	(0.47)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	-0.09^{***}	-0.09^{***}	-0.06^{**}	-0.06^{*}	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\mathbb{1}[\text{CareerExecutive}]_{id}$	0.08^{**}	0.08^{**}	0.02	0.02	-0.05^{*}	-0.05^{**}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)
$\mathbb{1}[\text{RequestIncluded}]_{id}$					83.63^{***}	83.65^{***}
					(1.97)	(1.97)
County & State-disaster FE	X	X	X	X	X	X
Fully specified		X		X		X
N	4539	4539	4539	4539	4539	4539
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.60	0.60	0.60	0.60	0.60	0.60

${}^{*}p < 0.10, {}^{**}p < 0.05, {}^{***}p < 0.01$

Notes: Table explores the differences in δ and λ from the existence of career executives. The dependent variables of each column are identical to those of Table 2.

Appendix Table B7. Mechanisms: Heterogenoeus response to PDA inclusion, depending on executives

	Characteristics of the executive:							
	Career executives				Non-career executives			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}[\text{RequestIncluded}]_{id}$	83.35***	84.07***	83.96***	81.52***	82.62***	80.36***	81.61***	81.85***
	(2.39)	(2.26)	(2.33)	(2.62)	(2.94)	(2.41)	(2.51)	(3.30)
$\mathbb{1}[\text{RequestIncluded}]_{id}\mathbb{1}[\text{CareerExec}]_{r(i),d}$	0.72	−2.16	−1.05	1.98				
	(3.22)	(3.00)	(3.05)	(3.56)				
$\mathbb{1}[\text{RequestIncluded}]_{id}\mathbb{1}[\text{NonCareerExec}]_{r(i),d}$					1.91	4.32	3.05	1.28
					(3.49)	(3.02)	(3.07)	(4.00)
FI_{id} cut-off	1.5-year	1.25-year	1.33-year	2-year	1.5-year	1.25-year	1.33-year	2-year
N	4543	5353	5025	3772	4543	5353	5025	3772
Dep. var.: Mean	0.34	0.31	0.32	0.37	0.34	0.31	0.32	0.37
R^2	0.87	0.86	0.86	0.87	0.87	0.86	0.86	0.87

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Notes: Table explores the heterogeneous response of the y_{2id} (ultimate receipt of PA) to y_{1id} (inclusion in PDA), depending on the existence of the career and non-career executives in FEMA regional office overseeing the disaster. Each column uses different thresholds for the flood intensity metric.

Appendix Table B8. Mechanisms: Disaster relief fund balance

	Included in assistance requests			Received public assistance					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FI_{id}	11.79***	30.55***	11.91***	10.71***	15.74	10.09***	0.51	−10.72	−0.24
	(2.25)	(10.98)	(2.33)	(2.33)	(13.61)	(2.48)	(0.89)	(6.91)	(1.04)
$\text{MarginPres}_{ie(d)}$	−7.30	−3.19	−0.06	−5.27	−4.17	0.50	1.05	−1.40	0.55*
	(7.26)	(8.04)	(0.59)	(7.43)	(8.20)	(0.62)	(2.43)	(2.85)	(0.30)
$\text{MarginPres}_{ie(d)}\mathbb{1}[\text{DRFHigh}]_d$			1.34			0.73			−0.43
			(0.99)			(1.08)			(0.49)
$\text{MarginPres}_{ie(d)}\log(\text{DRF})_d$	0.83	0.40		0.64	0.53		−0.08	0.18	
	(0.78)	(0.86)		(0.79)	(0.88)		(0.26)	(0.30)	
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	0.42	0.24	0.01	0.32	0.27	−0.02	−0.04	0.07	−0.03*
	(0.34)	(0.37)	(0.03)	(0.34)	(0.37)	(0.03)	(0.11)	(0.13)	(0.02)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\mathbb{1}[\text{DRFHigh}]_d$			−0.08			−0.04			0.02
			(0.05)			(0.05)			(0.02)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\log(\text{DRF})_d$	−0.05	−0.03		−0.04	−0.03		0.00	−0.01	
	(0.04)	(0.04)		(0.04)	(0.04)		(0.01)	(0.01)	
$\mathbb{1}[\text{RequestIncluded}]_{id}$							86.55***	86.64***	86.71***
							(2.53)	(2.54)	(2.51)
County & State-disaster FE	X	X	X	X	X	X	X	X	X
Fully specified		X	X		X	X		X	X
N	3605	3605	3605	3605	3605	3605	3605	3605	3605
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.64	0.64	0.64	0.63	0.63	0.63	0.89	0.89	0.89

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Notes: Table explores the role of disaster relief fund (DRF) balance at the advent of the disaseter in driving δ and λ heterogeneity. $\mathbb{1}[\text{DRFHigh}]_d$ is a dummy variable of the DRF being larger than the median level of the administration.

Appendix Table B9. Mechanisms: Election-year and battleground effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FI_{id}	9.58***	8.62***	0.63	9.55***	8.79***	0.81	10.07***	9.04***	0.63
	(1.73)	(1.84)	(0.78)	(1.86)	(1.93)	(0.79)	(1.97)	(2.06)	(0.90)
$\text{MarginPres}_{ie(d)}$	0.71**	0.88***	0.29**	0.72**	0.92***	0.32**	0.64*	0.90**	0.36**
	(0.32)	(0.32)	(0.14)	(0.33)	(0.32)	(0.14)	(0.37)	(0.38)	(0.16)
$\text{MarginPres}_{ie(d)}\mathbb{1}[\text{ElectionYear}]_d$	0.49	1.54	1.13***						
	(1.72)	(1.64)	(0.27)						
$\text{MarginPres}_{ie(d)}\text{Battleground}_{ie(d)}$				0.01	3.15	3.15			
				(4.71)	(4.89)	(2.78)			
$\text{MarginPres}_{ie(d)}\text{Battleground}_{s(i),e(d)}$							0.67	0.27	−0.29
							(1.22)	(1.16)	(0.48)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	−0.03**	−0.04***	−0.01**	−0.03**	−0.04***	−0.02**	−0.03*	−0.04**	−0.02**
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\mathbb{1}[\text{ElectionYear}]_d$	−0.02	−0.07	−0.05***						
	(0.07)	(0.07)	(0.01)						
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\text{Battleground}_{ie(d)}$				−0.01	−0.16	−0.15			
				(0.22)	(0.23)	(0.13)			
$\text{FI}_{id}\text{MarginPres}_{ie(d)}\text{Battleground}_{s(i),e(d)}$							−0.03	−0.01	0.01
							(0.06)	(0.05)	(0.02)
$\mathbb{1}[\text{RequestIncluded}]_{id}$			83.44***			83.52***			83.58***
			(1.97)			(1.97)			(1.96)
Dependent variable	y_{1id}	y_{2id}	y_{2id}	y_{1id}	y_{2id}	y_{2id}	y_{1id}	y_{2id}	y_{2id}
County & State-disaster FE	X	X	X	X	X	X	X	X	X
Control for request			X			X			X
Battleground status				County	County	County	State	State	State
N	4539	4539	4539	4539	4539	4539	4539	4539	4539
R^2	0.60	0.60	0.87	0.60	0.60	0.87	0.60	0.60	0.87

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Table explores the role of disaster occurring in a presidential election year ($\mathbb{1}[\text{ElectionYear}]_d$), the county being a battleground county ($\text{Battleground}_{ie(d)}$), being in a battleground state ($\text{Battleground}_{s(i),e(d)}$), in δ and λ.

Appendix Table B10. Mechanisms: Presidential partisanship and administrations

	(1)	(2)	(3)	(4)	(5)	(6)
FI_{id}	9.83***	8.75***	0.54	6.31***	5.66**	0.38
	(1.86)	(1.96)	(0.89)	(2.15)	(2.31)	(1.55)
$\mathrm{MarginPres}_{ie(d)}$	1.67	2.00**	0.61	1.84	2.10**	0.56
	(1.02)	(0.93)	(0.47)	(1.17)	(1.03)	(0.57)
$\mathrm{MarginPres}_{ie(d)}\mathrm{RepublicanPres}_d$	−2.03	−2.22	−0.52			
	(1.87)	(1.90)	(1.00)			
$\mathrm{MarginPres}_{ie(d)}\mathrm{ObamaAdmin1}_d$				1.23	1.67*	0.64
				(1.27)	(0.93)	(0.86)
$\mathrm{MarginPres}_{ie(d)}\mathrm{ObamaAdmin2}_d$				−0.14	0.12	0.24
				(1.29)	(1.46)	(1.06)
$\mathrm{MarginPres}_{ie(d)}\mathrm{TrumpAdmin1}_d$				−2.96	−3.10	−0.63
				(2.03)	(2.08)	(1.08)
$\mathrm{FI}_{id}\mathrm{MarginPres}_{ie(d)}\log(\mathrm{FEMACareer})_d$	0.09	0.10	0.02			
	(0.09)	(0.09)	(0.05)			
$\mathrm{FI}_{id}\mathrm{MarginPres}_{ie(d)}\mathrm{ObamaAdmin1}_d$				−0.06	−0.08*	−0.03
				(0.06)	(0.05)	(0.04)
$\mathrm{FI}_{id}\mathrm{MarginPres}_{ie(d)}\mathrm{ObamaAdmin2}_d$				0.01	−0.01	−0.01
				(0.06)	(0.07)	(0.05)
$\mathrm{FI}_{id}\mathrm{MarginPres}_{ie(d)}\mathrm{TrumpAdmin1}_d$				0.11	0.12	0.03
				(0.09)	(0.10)	(0.05)
$\mathbb{1}[\mathrm{RequestIncluded}]_{id}$			83.54***			83.54***
			(1.97)			(2.00)
Dependent variable	y_{1id}	y_{2id}	y_{2id}	y_{1id}	y_{2id}	y_{2id}
County & State-disaster FE	X	X	X	X	X	X
N	4539	4539	4539	4539	4539	4539
R^2	0.60	0.60	0.87	0.60	0.60	0.87

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

Notes: Table explores the role of the president's party and the individual administration in driving δ and λ coefficients. The base case for the administration variable is the disasters in the Biden Administration.

Appendix Table B11. Mechanisms: House oversight committee ranking membership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FI_{id}	8.37***	8.37***	8.79***	8.43***	9.04***	8.51***	9.61***	9.12***
	(1.99)	(1.99)	(1.78)	(1.87)	(1.83)	(1.93)	(1.79)	(1.92)
$\text{MarginPres}_{ie(d)}$	1.01**	1.01**	1.06**	1.12***	0.92**	0.90**	0.77*	0.82*
	(0.44)	(0.44)	(0.43)	(0.42)	(0.43)	(0.42)	(0.42)	(0.42)
$\text{MarginPres}_{ie(d)}\text{AnyCommittee}_{st}$	0.01	0.01						
	(0.82)	(0.82)						
$\text{MarginPres}_{ie(d)}\text{InfraCommittee}_{st}$			−0.83	−0.27				
			(0.86)	(0.84)				
$\text{MarginPres}_{ie(d)}\text{AppropCommittee}_{st}$					−0.46	0.36		
					(0.86)	(0.84)		
$\text{MarginPres}_{ie(d)}\text{HomelandCommittee}_{st}$							−0.53	0.66
							(1.17)	(1.28)
$FI_{id}\text{MarginPres}_{ie(d)}$	−0.05**	−0.05**	−0.05**	−0.06***	−0.04**	−0.04**	−0.04*	−0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$FI_{id}\text{MarginPres}_{ie(d)}\text{AnyCommittee}_{st}$	0.00	0.00						
	(0.04)	(0.04)						
$FI_{id}\text{MarginPres}_{ie(d)}\text{InfraCommittee}_{st}$			0.05	0.02				
			(0.04)	(0.04)				
$FI_{id}\text{MarginPres}_{ie(d)}\text{AppropCommittee}_{st}$					0.03	−0.01		
					(0.04)	(0.04)		
$FI_{id}\text{MarginPres}_{ie(d)}\text{HomelandCommittee}_{st}$							0.02	−0.03
							(0.05)	(0.06)
Dependent variable	y_{1id}	y_{2id}	y_{1id}	y_{2id}	y_{1id}	y_{2id}	y_{1id}	y_{2id}
County & State-disaster FE	X	X	X	X	X	X	X	X
N	4539	4539	4539	4539	4539	4539	4539	4539
R^2	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Notes: Table explores the existence of a state representative being present in the House of Representative's committee overseeing FEMA.

Appendix Table B12. Mechanisms: FEMA staffing levels

	(1)	(2)	(3)	(4)	(5)	(6)
FI_{id}	−19.54	−58.50	−42.18	36.54	−10.63	−41.16
	(154.11)	(160.31)	(74.85)	(144.65)	(149.08)	(62.75)
$\text{MarginPres}_{ie(d)}$	−25.26	−41.40	−20.30	−13.54	−22.14	−10.83
	(58.52)	(64.64)	(34.50)	(57.63)	(59.77)	(32.42)
$\text{MarginPres}_{ie(d)} \log(\text{FEMACareer})_d$	3.10	5.05	2.46			
	(6.99)	(7.72)	(4.12)			
$\text{MarginPres}_{ie(d)} \log(\text{FEMAAllStaff})_d$				1.68	2.72	1.32
				(6.80)	(7.06)	(3.82)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	1.30	2.20	1.11	0.87	1.34	0.62
	(2.76)	(3.06)	(1.65)	(2.78)	(2.84)	(1.60)
$\text{FI}_{id}\text{MarginPres}_{ie(d)} \log(\text{FEMACareer})_d$	−0.16	−0.27	−0.13			
	(0.33)	(0.37)	(0.20)			
$\text{FI}_{id}\text{MarginPres}_{ie(d)} \log(\text{FEMAAllStaff})_d$				−0.11	−0.16	−0.08
				(0.33)	(0.34)	(0.19)
$\mathbb{1}[\text{RequestIncluded}]_{id}$			83.54^{***}			83.54^{***}
			(1.97)			(1.97)
Dependent variable	y_{1id}	y_{2id}	y_{2id}	y_{1id}	y_{2id}	y_{2id}
Control for request			X			X
County & State-disaster FE	X	X	X	X	X	X
N	4539	4539	4539	4539	4539	4539
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22
FI_{id}: Mean	20.70	20.70	20.70	20.70	20.70	20.70
FI_{id}: SD	1.64	1.64	1.64	1.64	1.64	1.64
R^2	0.60	0.60	0.87	0.60	0.60	0.87

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Table explores the role of staffing levels of FEMA in δ and λ, using the log of total number of FEMA career staffs and the log of all (career and non-career) FEMA staffs.

Appendix Table B13. Mechanisms: Different types of public assistance

	(1) A – Debris removal	(2) B – Protective measures	(3) C – Roads and bridges	(4) D – Water control facilities
FI_{id}	−0.98	16.93	13.58	90.40*
	(21.36)	(17.62)	(13.10)	(51.23)
$MarginPres_{ie(d)}$	5.45	5.83**	2.99	4.12
	(3.44)	(2.75)	(1.83)	(8.17)
$FI_{id}MarginPres_{ie(d)}$	−0.25	−0.29**	−0.16*	−0.13
	(0.16)	(0.12)	(0.09)	(0.32)
N	859	1059	1422	370
Dep. var.: Mean	10.60	10.59	12.48	11.29
R^2	0.89	0.88	0.84	0.87
	(5) E – Public Buildings	(6) F – Public utilities	(7) G – Recreational or other	
FI_{id}	70.32	50.24	−14.86	
	(93.49)	(39.81)	(23.06)	
$MarginPres_{ie(d)}$	9.28	1.74	20.79***	
	(17.72)	(10.69)	(6.74)	
$FI_{id}MarginPres_{ie(d)}$	−0.49	−0.12	−0.92***	
	(0.79)	(0.45)	(0.29)	
N	297	543	525	
Dep. var.: Mean	10.19	10.89	10.72	
R^2	0.99	0.89	0.93	

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Table explores political bias in different aspects of the public assistance by fitting (2) against different components of the PA.

Appendix Table B14. Robustness check: Clustering levels and time-varying covariates, including all W_{id} coefficient estimates

	Dependent variable:					
	Included in assistance requests			Received public assistance		
	(1)	(2)	(3)	(4)	(5)	(6)
FI_{id}	9.91***	10.06***	81.14	9.09***	9.20***	52.38
	(1.55)	(1.73)	(56.27)	(1.71)	(1.83)	(63.88)
$\text{MarginPres}_{ie(d)}$	0.72***	0.82**	0.82**	0.93***	1.02***	1.04***
	(0.23)	(0.34)	(0.33)	(0.25)	(0.33)	(0.33)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	−0.03***	−0.04**	−0.04**	−0.04***	−0.05***	−0.05***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
PopDensity_{it}		−0.17***	−0.22		−0.15*	−0.21
		(0.04)	(0.21)		(0.09)	(0.22)
% Elderly_{it}		2.29**	−2.28		1.75*	−3.23
		(1.00)	(5.89)		(0.99)	(6.13)
$\log(\text{Income})_{it}$		−12.00	120.59		−10.68	73.04
		(13.54)	(101.43)		(14.69)	(114.84)
$\text{FI}_{id}\text{PopDensity}_{it}$			0.00			0.00
			(0.01)			(0.01)
FI_{id}% Elderly_{it}			0.23			0.25
			(0.29)			(0.31)
$\text{FI}_{id} \log(\text{Income})_{it}$			−6.91			−4.37
			(5.36)			(6.08)
County & State-disaster FE	X	X	X	X	X	X
W_{it} included		X	X		X	X
$W_{it}\text{FI}_{it}$ included			X			X
Alternative SE clustering	X			X		
N	4539	4539	4539	4539	4539	4539
R^2	0.60	0.60	0.60	0.60	0.60	0.60

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Notes: Table shows all coefficients for the variables shown in Table 4.

Appendix Table B15. Robustness check: Alternative flooding intensity metrics, assistance requested (y_{1id})

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FI_{id}	9.91***	7.99***	7.99***	7.35***	7.26***	5.70***	5.39**	9.80***
	(1.74)	(1.30)	(1.50)	(1.66)	(1.93)	(2.12)	(2.39)	(1.76)
$\mathrm{MarginPres}_{ie(d)}$	0.72**	0.51*	0.61**	0.81**	0.77*	0.77	0.64	0.28
	(0.33)	(0.29)	(0.31)	(0.34)	(0.42)	(0.52)	(0.60)	(0.18)
$\mathrm{FI}_{id}\mathrm{MarginPres}_{ie(d)}$	−0.03**	−0.02	−0.03*	−0.04**	−0.04*	−0.04	−0.03	−0.03
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
FI_{it} cut-off	1.5-year	1.25-year	1.33-year	2-year	3-year	4-year	5-year	1.5-year
Damage metric used	Housing	Housing	Housing	Housing	Housing	Housing	Housing	Population
N	5232	6127	5776	4401	3510	2927	2523	5232
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
FI_{it}: Mean	20.67	20.67	20.66	20.61	20.51	20.47	20.40	9.73
FI_{it}: SD	1.63	1.64	1.64	1.61	1.59	1.57	1.58	1.46
R^2	0.56	0.53	0.54	0.60	0.66	0.71	0.74	0.56

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Notes: Table tests the robustness of the results for (1) to using different thresholds for defining the FI_{id} variable (columns 2 to 7) and to using population of the census tract affected, instead of housing value, as the source of FI_{id}.

Appendix Table B16. Robustness check: Alternative flooding intensity metrics, assistance received (y_{2id})

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FI_{id}	9.09***	7.84***	7.45***	8.07***	8.97***	7.84***	6.28**	9.46***
	(1.84)	(1.30)	(1.55)	(1.73)	(2.17)	(2.29)	(2.64)	(1.95)
$\text{MarginPres}_{ie(d)}$	0.93***	0.77**	0.82***	1.05***	1.08**	0.83	0.25	0.41**
	(0.33)	(0.30)	(0.31)	(0.37)	(0.43)	(0.55)	(0.65)	(0.18)
$\text{FI}_{id}\text{MarginPres}_{ie(d)}$	−0.04***	−0.04**	−0.04**	−0.05***	−0.05**	−0.04	−0.01	−0.04**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
FI_{it} cut-off	1.5-year	1.25-year	1.33-year	2-year	3-year	4-year	5-year	1.5-year
Damage metric used	Housing	Housing	Housing	Housing	Housing	Housing	Housing	Population
N	5232	6127	5776	4401	3510	2927	2523	5232
Dep. var.: Mean	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22
FI_{it}: Mean	20.67	20.67	20.66	20.61	20.51	20.47	20.40	9.73
FI_{it}: SD	1.63	1.64	1.64	1.61	1.59	1.57	1.58	1.46
R^2	0.56	0.53	0.54	0.60	0.66	0.71	0.74	0.56

$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$

Notes: Table tests the robustness of the results for (2) to using different thresholds for defining the FI_{id} variable (columns 2 to 7) and to using population of the census tract affected, instead of housing value, as the source of FI_{id}.