The Unintended Consequences of Post-Disaster Policies for Spatial Sorting

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Marcel Henkel  
University of Bern, CRED

Eunjee Kwon  
University of Cincinnati, Real Estate, Dep of Finance

Pierre Magontier  
University of Bern / Universitat de Barcelona, CRED / IEB

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Abstract

Post-disaster aid aims to relieve affected communities, but excessive bailouts may encourage economic activity to remain in exposed areas. We provide new empirical and theoretical evidence on the spatial consequences of post-disaster policies related to political motives. Using the exogenous variation in the timing of natural disasters, we show that hurricanes close to Election Day lead to increased post-disaster efforts at the local level and result in increased population sorting into the impacted areas. To quantify and comprehend the implications of this new sorting pattern for the aggregate economy, we introduce the relationship between electoral cycles and post-disaster policies as a new feature in a dynamic spatial general equilibrium model. We show that households respond to current post-disaster policies by sorting in hazard-prone coastal areas. Under the assumption of no climate change, current post-disaster policies improve aggregate welfare at the expense of overall GDP and productivity losses.

Key words: Natural Disasters, Political Budget Cycles, Spatial Sorting

JEL classification: Q54, D72, H53, H84
1 Introduction

Most developed countries provide relief funding to address the negative impact of natural disasters on the local economy. In the United States, the Disaster Relief Fund operated by the Federal Management Emergency Agency (FEMA) serves this purpose. The costs of catastrophic events\(^1\) drive the largest share of its total funding and accumulated to 296 billion dollars between January 2001 and November 2019. The media have traditionally emphasized these astonishing figures to underline the increasing intensity and frequency of natural disasters or illustrate state interventionism. Yet, counties struck by major hurricanes – which are notable catastrophic events – experienced a remarkable population increase of 27.4\% on average during the same period (i.e., 49,224 more individuals per county). In comparison, the continental U.S. coastal population grew by only 14.9\%.\(^2\)

How do post-disaster policies affect the spatial distribution of economic activity? Do they encourage moving away from hazards or adversely sorting in exposed areas?

Post-disaster programs become a particularly salient policy matter for many political candidates when large disasters occur amid an electoral campaign.\(^3\) Incumbents are encouraged to boost post-disaster efforts as an election approaches. However, there is a trade-off between providing legitimate aid to affected populations and encouraging more people and capital to stay in hazardous areas. Transfers to regions affected by natural disasters can revitalize the local economy and deter workers and businesses from relocating. If individuals remain unprepared because of moral hazard or myopic foresight, post-disaster policies could lead to even more severe future consequences.

In this paper, we identify the impact of the electoral cycle on local post-disaster efforts and the subsequent consequences on the spatial distribution of economic activities. To this end, we exploit the timing of hurricanes’ landings relative to Election Day\(^4\) as an exogenous variation of natural disasters with greater electoral importance. Election day

\(^1\) Catastrophic events are defined as events incurring more than 500 million dollars in costs. ‘The Disaster Relief Fund: Overview and Issues’ Congressional Research Service (11/13/2020) — https://fas.org/sgp/crs/homesec/R45484.pdf.

\(^2\) The number is calculated using the CLIMADA wind field distributions, the 2000 and 2020 American Census and the census’ list of coastal counties.

\(^3\) Previous literature has shown that natural disasters could lead to substantial increases in the federal welfare program (Deryugina, 2017).

\(^4\) These elections are first and foremost interesting because they happen every other year and directly affect the composition of the Congress, which votes on different budgetary accounts such as the Disaster Relief Fund. Indeed, every two years, the entire House of Representatives and a third of the Senate are renewed. Voters generally decide on many other federal offices on that same day, such as the Presidential office (every four years), and depending on the location, gubernatorial and local offices as well.
takes place on the first Tuesday of November in even years. Because hurricane season occurs between June and November, it is then a salient electoral matter every other year. Additionally, whether hurricanes’ timing is concurrent with Election Day is arguably exogenous, giving us an adequate empirical setting to leverage variation in post-disaster policy efforts. Conditional on location and time fixed-effects, the quasi-random trajectory of hurricanes implies that we can take the exact place and landfall of a hurricane as exogenous.

Using the timing of hurricanes as an exogenous shock, we apply the recent advances in the difference-in-difference literature (Callaway and Sant’Anna, 2020) to study the local budgets’ responses to natural disasters and the subsequent population sorting. To achieve this analysis, we employ an event-study approach to estimate the dynamic consequences of hurricanes occurring less than a year before Election Day (i.e., ‘on-cycle’ hurricanes) and hurricanes occurring more than a year before Election Day (i.e., ‘off-cycle’).

Our empirical findings using county-level data between 2001 and 2019 are as follows. First, we document that the number of days between a hurricane hit and the next Election Day is a good predictor of local post-disaster efforts. We show that counties hit by on-cycle hurricanes spend more than they collect in taxes, indicating higher governmental layers’ transfers might support them. However, net spending in counties hit by off-cycle hurricanes remains unaffected by the shock. We further show that counties hit by on-cycle disasters receive more than twice as much funding in post-disaster grants per capita from FEMA – particularly to public administrations, than counties hit by off-cycle hurricanes. This relation is robust to including a series of controls and is in line with the literature on electoral incentives and post-disaster efforts (Healy and Malhotra, 2009; Besley and Burgess, 2002; Strömberg, 2004; Cole et al., 2012).

We then demonstrate that on-cycle hurricanes lead to a significant and long-lasting increase in population, indicating that individuals sort into affected areas after an on-cycle disaster. The average treatment effect of on-cycle hurricanes on population is about 4.7%. On the other hand, the size of the overall population remains unaffected by off-cycle hurricanes. The results suggest that electoral incentives of post-disaster efforts lead to an unintended consequence of population sorting into the affected areas. Finally, we do not observe the pre-trend in population growth between areas hit by on-cycle and off-cycle hurricanes, which supports the validity of our identification strategy. Importantly,
these results remain qualitatively similar when using alternative estimators or control 
groups, controlling for storm intensity, or considering more extended periods or other 
extreme natural disasters such as floods or wildfires. Using alternative political dimensions 
(e.g., political alignment) instead of electoral cycles supports the hypothesis that electoral 
incentives strongly affect spatial sorting patterns.

To quantify and comprehend the implications of this new sorting pattern for the ag-
gregate economy, we introduce a dynamic spatial general equilibrium model integrating 
a relationship between political cycles and post-disaster policies. The model provides a 
simple setup to explore the role of post-disaster policies and electoral incentives in the 
spatial distribution of economic activity. In doing so, we build on Desmet et al. (2021) 
but make two critical amendments by adding the decision of public sectors. First, govern-
ments in every region provide local public services, and a fiscal transfer scheme reallocates 
resources across jurisdictions. Second, the amount of transfers and subsequent endogenous 
amenities a region receives in a given period depends on being hit by a disaster shock and 
the electoral cycle.

We simulate our model forward for 80 years, keeping current climate conditions un-
changed. We use a ‘short’ simulation period to acknowledge the difficulty of simulating the 
far future fundamental amenity distribution and the subsequent adaptation scenarios. We 
are also unsure about the design of future political and electoral institutions. Finally, we 
avoid modeling climate change scenarios, as the evolution of both frequency and intensity 
of future hurricanes is unlikely to change drastically before at least 50 to 100 years in the 
North-Atlantic basin and is still subject to discussion among meteorologists and climate 
scientists (Emanuel, 2011; Knutson et al., 2020). In our first counterfactual scenario, we 
remove the impact of post-disaster policies driven by electoral incentives by turning off the 
additional effect of on-cycle disasters. In our second counterfactual scenario, we entirely 
remove the impact of post-disaster programs on transfers and endogenous amenities.

We show that, compared to these counterfactuals, current post-disaster policies fea-
turing electoral cycles lead to population sorting from rich (high-productive) to relatively 
poor (low-productive) locations, thus lowering average productivity and real GDP at the 
national level. However, negative congestion externalities and the transformation of pub-
lic funds into higher-quality amenities matter, such that, without other disasters, current 
disaster policies improve aggregate welfare. However, the simulations also reveal that a
direct consequence of the current system is to push economic activity toward hazard-prone coastal areas. Accounting for other climate change consequences, such as sea-level rise, would likely result in mitigated welfare gains as these post-disaster efforts would, at least partially, go underwater.

Our paper contributes to the literature in several ways. Above all, this paper provides both new empirical and theoretical evidence on the unintended consequences of the electoral incentives of post-disaster efforts. The literature on government responsiveness and disaster aids has documented that natural disasters with higher electoral accountability lead to increased efforts of policymakers (Besley and Burgess, 2002; Strömberg, 2004; Eisensee and Strömberg, 2007; Gagliarducci et al., 2019). There has been a separate discussion on the spatial sorting of economic activity after extreme weather events (Dell et al., 2014; Boustan et al., 2012; Deryugina et al., 2018; Jerch et al., 2020; Boustan et al., 2020; Tran et al., 2020). We combine the two pieces of literature by showing that hurricanes with higher electoral incentives convey greater post-disaster efforts to the affected areas, which unintentionally contributes to the spatial sorting of economic activities. In doing so, we add to the literature on the welfare consequences of resources allocation (Sieg and Yoon, 2017; Finan and Mazzocco, 2021) by focusing on the spatial distribution of the economy. Secondly, we enrich the literature by providing methodological contributions, both empirically and theoretically. First, to causally estimate the impact of post-disaster policies on spatial sorting, we introduce the timing of hurricanes relative to the electoral cycle as a novel source of exogenous variation in disaster policy efforts. We also apply the recent advances of the difference-in-difference methods (Borusyak and Jaravel, 2017; Sun and Abraham, 2020; Callaway and Sant’Anna, 2020) for estimating the staggered treatment effects of the on-cycle hurricanes on the spatial sorting of economic activities. Theoretically, we extend an economic geography dynamic spatial equilibrium framework (Desmet et al., 2018; Kleinman et al., 2021) by including a government sector (Henkel et al., 2021) and a political economy feature in the form of electoral incentives, which, to the extent of our knowledge, is a novel attempt in the literature. Finally, we believe that this paper sheds light on the public debate by providing evidence on the frequently debated inefficiencies of the current post-disaster policies and their subsequent welfare implications.

The remaining chapters are as follows. Section 2 summarizes the related literature
in more details. Section 3 introduces the specificity of hurricanes and the institutional background of post-disaster policies in the US. Section 4 summarizes the data sources. Section 5 presents our empirical strategy and results. Section 6 develops the dynamic spatial general equilibrium model that we use to interpret the empirical findings. Section 7 describes the quantification of the model, while Section 8 documents the counterfactual analysis; and finally, Section 9 concludes.

2 Related Literature

This paper builds on several growing strands of literature at the intersection of economic geography, public, and environmental economics.

First, the statistical mechanisms used in this work were inspired by the literature on government responsiveness and disaster aid. In general, the design of institutions, and in particular the design of electoral institutions, plays a major role in the allocation of resources in the economy (Sieg and Yoon, 2017; Finan and Mazzocco, 2021). It has been extensively demonstrated that policymakers increase expenditures and postpone tax increases close to an election (Rogoff, 1987; Rogoff and Sibert, 1988; Besley and Case, 1995) or when their action receives significant media attention (Snyder Jr and Strömberg, 2010). In particular, when electoral accountability is high and a natural disaster occurs, policymakers tend to provide more calamity relief (Besley and Burgess, 2002; Strömberg, 2004; Eisensee and Strömberg, 2007; Healy and Malhotra, 2009) and pass more green bills (Gagliarducci et al., 2019; Kahn, 2007). For instance, the seminal work by Besley and Burgess (2002) shows that politicians are more responsive to flood losses via food distribution and relief expenditures when electoral accountability is high, in the case of India. Building on the latter, Cole et al. (2012) find that governments respond to the voters’ expectations by delivering more assistance during election years. Deryugina (2017) claims that natural disasters even lead to a significant increase in non-disaster transfers to affected areas, which generally exceeds disaster-related aid. Healy and Malhotra (2009) documents the voters’ side of the response to post-disaster policies and argues that voters do not reward incumbent governments for future disaster mitigation investments because they lack a disaster counterfactual to assess the policy. They do reward governments, however, for post-disaster relief. This present work exploits related political economy

See Alesina et al. (1997) for a review.
mechanisms – namely, the timing of hurricanes to the next election, as a tool to leverage exogenous variation in post-disaster efforts.

Second, our paper builds on the literature related to the spatial sorting of economic activity as a response to a natural disaster. This sorting operates through two main channels: risk perceptions and local economic impacts. As for the former channel, individuals seem to have a short-sighted understanding of disaster risks in hazardous areas. The literature concerning risk perceptions studies how different groups perceive heightened climate risks and how ideological factors influence spatial sorting (Howe et al., 2015; Bakkensen and Barrage, 2017; Gibson and Mullins, 2020; Bakkensen and Ma, 2020). For instance, households’ exposure to sea-level rise seems to be strongly driven by partisan ideas about climate change instead of the actual risks (Bernstein et al., 2020). Generally, Gallagher (2014) documents that after a historical inundation, the spike in households’ flood insurance take-up rate lasts less than a decade. Post-disaster aid to individuals seems even to curb the take-up rates of private insurance (Kousky et al., 2018). With the perceived low risk of disaster, households living in a risky area may not be willing to pay half of the median insurance premium (Netusil et al., 2020). Coastal home investments may encourage individuals to undertake collective disaster mitigation investments, but these actions may motivate more individuals to stay in place (McNamara and Keeler, 2013). These risk misperceptions, cumulated with insurance mispricing and local financial lenders’ shrouding risk behaviors, play a role in stimulating spatial sorting in hazardous areas (Ouazad and Kahn, 2019). Later, we build on this literature to argue how individuals react to the increased amenities generated by the post-disaster policies and yet appear to ignore these inherent local risks.

Still, natural disasters could also impact the sorting of economic activity through local economic effects. Several papers investigate how natural hazards affect spatial sorting through their economic impacts (Strobl, 2011; Boustan et al., 2012; Mahajan and Yang, 2020; Hornbeck, 2012; Hauer, 2017; Desmet et al., 2015, 2021). In particular, Hornbeck (2012) documents how the U.S. Dust Bowl permanently affected agricultural land values in the 1930s and how the labor market adjusted primarily through population out-migration. Overall, however, there is less consensus in the literature on how catastrophic events affect the sorting responses of economic activities. Kocornik-Mina et al. (2020) argue

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6 FEMA was not created until 1979, under the Carter administration.
that large floods do not shift economic activities away from the hazardous areas, mainly because the sunk costs of investment in the locations play a more significant role than information updating regarding hazards. Likewise, Spitzer et al. (2020) finds that when a non-permanent shock occurs, people usually remain in the affected areas or return quickly after the disaster, as the shock is perceived as a low risk of reoccurring. Gallagher and Hartley (2017) shows that Hurricane Katrina’s flooding did not significantly impact most households’ finances, and only the most flooded used their flood insurance to pay down their mortgage rather than rebuild. While individuals might struggle with harsh economic consequences, generous post-disaster policies could also curb migration away from hazards, as individuals are attached to their neighborhood economic and social ties (Paxson and Rouse, 2008). Using the latest difference-in-difference techniques, we show that previous research could have underestimated such a sorting response as we find that post-disaster efforts encourage economic activity to remain in hazardous places.

Third, this paper relates to the impact of natural disasters on local public finances and local multipliers. In recent work, Jerch et al. (2020) explore the dynamic effects of hurricanes on local public finances and find that large disasters increase local budgets’ deficits by reducing expenditures and tax revenues. Therefore, instruments designed to alleviate the consequence of natural hazards, such as relief policies, can influence the sorting of economic activities in the longer run by substituting local spending and generating a local multiplier effect (Chodorow-Reich, 2019). Corbi et al. (2019) shows in the case of Brazilian municipalities, an exogenous shift in federal transfers to local governments leads to a significant boost in employment and increased firm entry. We follow up on this idea by illustrating how heightened post-disaster efforts are concurrent with larger local budget deficits.

Finally, our work resonates with the economic geography of natural disasters and climate change (Desmet et al., 2015, 2018, 2021; Kleinman et al., 2021; Fried, 2021). While the role of this paper is not to quantify the long-run impact of global or localized hazards on adaptation to climate change, we provide an attempt to illustrate the trade-offs generated by post-disaster policies in a spatial framework. Later we rely extensively on this literature to structurally represent the economy. We depart from it by integrating a redistribution scheme influenced by electoral forces, as described in the first paragraph of this section.
3 Hurricane and Post-Disaster Policies

To better understand the context in which our empirical framework operates, we provide in this section background information about hurricanes – a sub-class of tropical storms, and the institutional design surrounding post-disaster programs in the United States.

3.1 Hurricanes in the United States

Tropical origins and season – Hurricanes are tropical cyclones forming in the Atlantic Basin characterized by a rotating storm system involving high winds and a low-pressure center. They typically form as moisture starts to rise above the water, generally in areas of pre-existing low-pressure. This process requires waters to reach temperatures of at least 26 °C (80 °F), which, in the Atlantic, happens in tropical or subtropical regions during the summer. As moisture rises, it attracts more air above the water, causing more moisture to ascend. Large, heavy clouds form as the humid air cools off, and because of Earth’s spin and the Coriolis effect, the storm starts rotating counterclockwise and generally moving west. During the late summer season, vertical wind shear is less present, thus favoring the creation of cyclones with appropriate conditions of heat and humidity. According to the National Center for Atmospheric Research, hurricanes can be up to 600 miles (ca. 966 kilometers) long and have powerful gusts spiraling upward from 75 mph (ca. 121 kilometers per hour) to 200 mph (ca. 322 kilometers per hour). They usually last for over a week, moving 10-20 miles per hour over the open ocean. When the cyclone makes landfall, it loses its fuel – the ocean moisture, and quickly vanishes. Because of the conditions mentioned above, the hurricane season spans between June and November in the North Atlantic basin.

Classification and Frequency – Like most natural disasters, hurricanes do not simply appear. Instead, they are specific storms that have evolved from milder conditions. In particular, a hurricane is a tropical storm that is a type of tropical depression. A tropical depression is classified as a tropical storm when maximum sustained winds reach 39 miles per hour (ca. 63 kilometers per hour). The Saffir–Simpson scale categorizes hurricanes on a 1-to-5 scale based on the maximum 1-minute sustained winds (which does not account for other related hazards, such as storm surge or heavy rainfall). A tropical storm becomes

\footnote{https://www.nhc.noaa.gov/pdf/sshws_table.pdf}
Table 1: **Historical Hurricanes in the North Atlantic Basin (1851-2019)**

<table>
<thead>
<tr>
<th></th>
<th>Tropical Storms</th>
<th>Hurricanes</th>
<th>Major Hurricanes</th>
<th>U.S. Hurricanes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Numbers</td>
<td>1,625</td>
<td>917</td>
<td>315</td>
<td>294</td>
</tr>
<tr>
<td>Annual Mean</td>
<td>9.67</td>
<td>5</td>
<td>1.875</td>
<td>1.75</td>
</tr>
<tr>
<td>Annual Median</td>
<td>9</td>
<td>5</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Annual Max</td>
<td>28</td>
<td>15</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Annual Min</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: (i) Summary statistics extracted from the North Atlantic Hurricane Basin (1851-2019) Comparison of Original and Revised HURDAT from NOAA. (ii) All columns report summary statistics about tropical storms that have formed in the North Atlantic Basin broken down into different categories: tropical storms ($\geq 39$ mph), hurricanes ($\geq 73$ mph), and major hurricanes ($\geq 111$ mph). U.S. hurricanes are hurricanes that made landfall in the U.S. (iii) Mean, median, maximum, and minimum are defined on an annual basis.

A category one hurricane when winds get up to 73 mph (ca. 117 kilometers per hour). A ‘major’ hurricane is of category three ($\geq 111$ mph (ca. 179 kilometers per hour)) or above. A hurricane enters the top category – category 5 when maximum sustained winds reach 157 mph (ca. 253 kilometers per hour). Examples of category five hurricanes include Dorian, who caused large fatalities and destruction to the Bahamas in 2019, and Andrew, who struck Louisiana and Florida in 1992. Table 1 summarizes the number of historical hurricanes in the North Atlantic Basin from 1851 to 2019. While almost ten tropical storms form every year in the North Atlantic Basin, on average, 1.75 hurricanes have made landfall in the United States since 1851. The average return period varies greatly depending on the location – from 5 years in South Carolina or Florida to 20 years in New Jersey and Southern Texas. In this paper, we focus on the impact of hurricanes (i.e., rotating storm systems characterized by at least 73 mph maximum winds) that made landfall in the United States Atlantic coast between 2001 and 2019.

**Consequences** – Hurricanes are not only dangerous for their high-wind velocities. They usually come with other natural hazards, including extreme rainfall, storm surges, tornadoes, and floods. These direct costs pile up on indirect consequences, such as disease outbreaks caused by the disruption of essential emergency services. While hurricanes remain rare compared to other disasters, they are exceptionally costly. Since 1980, the United States has experienced 258 weather disasters with 1.875 trillion dollars of total costs. Among these disasters, tropical cyclones cost the U.S. economy $945.9 billion in

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8[https://www.aoml.noaa.gov/hrd/hurdat/comparison_table.html](https://www.aoml.noaa.gov/hrd/hurdat/comparison_table.html)  
9[https://www.nhc.noaa.gov/climo/images/return_hurr.jpg](https://www.nhc.noaa.gov/climo/images/return_hurr.jpg)
total, with an average cost of almost $21.5 billion per event. Of all natural hazards, they were responsible for the highest number of deaths: 6,593 between 1980 and 2020.\(^\text{10}\)

3.2 Post-Disaster Policies in the United States

Disaster Declaration — While states’ governors can issue declarations of disaster, states do not generally provide substantial relief (Sylves, 2019). To access federal support, states must first request a Presidential Declaration of Disaster (PDD). The Stafford Act of 1988 defined a ‘major disaster’ as ‘any natural catastrophe ... or, regardless of cause, any fire, flood, or explosion, in any part of the United States, which in the determination of the President causes damages of sufficient severity and magnitude to warrant major disaster assistance.’ The President has considerable discretionary powers over post-disaster policy implementation with this definition. As specified by the 1988 amendment, a PDD identifies counties eligible for federal assistance and the associated grant programs. These programs make state, tribal, and local governments, and individuals eligible for relief or preparation funds, most of which are financed by the Disaster Relief Fund (DRF). Interestingly, events incurring more than 500 million dollars in costs (such as hurricanes) rather than the volume of presidentially declared ‘major disasters’ drive the DRF funding. This account is funded by Congress and managed by the Federal Emergency Management Administration (FEMA). Other post-disaster programs exist, such as the Small Business Administration loans, but FEMA remains historically the largest provider of post-disaster assistance.

Procedures — FEMA post-disaster grants can be classified into two broad categories: relief vs. preparedness and public vs. private grants. They vary in their degree of competitiveness and conditions to qualify. For instance, in the case of grants available to local governments (public), State emergency management agencies must send FEMA a letter of intent indicating whether the State will request funds. Local governments and state agencies interested in applying for the funds must write an application project for the properties they think need to receive mitigation (e.g., road elevation) or relief work (e.g., debris removal). Individuals and businesses are not eligible for such funds, but they may request their local representatives to apply on their behalf.

\(^{10}\)https://coast.noaa.gov/states/fast-facts/hurricane-costs.html
State emergency management agencies then review applications for general eligibility, project cost-effectiveness, feasibility, and environmental compliance. They are also in charge of prioritizing projects when the requested amounts would be higher than the total budget. All applications must be submitted to FEMA by State emergency management agencies within the 12 months following a Presidential Declaration of Disaster. FEMA then officially selects projects following the State’s agency priorities, subject to the total allocated amount. The federally-obligated share amounts at least 75 percent of the total project amount. The remaining 25 percent is split between non-federal entities.

In the case of individual assistance, FEMA provides compensation to disaster survivors to meet their basic needs. However, this help is strictly regulated and enforced. For instance, the Individual Assistance program run by FEMA does not substitute for private insurance and the compensation extent varies with other criteria such as whether an individual is eligible for other sources of funding (e.g., from the Small Business Administration).

4 Data

To investigate the relation between post-disaster policies and sorting responses of economic activity, we collect yearly data from the International Best Track Archive for Climate Stewardship (IBTrACS), the Surveillance Epidemiology and End Results (SEER) population database, the Bureau of Economic Analysis (BEA), and The Government Finance Database, at the county level in the U.S. between 2001 and 2019.

4.1 Data Sources

International Best Track Archive for Climate Stewardship (IBTrACS) — The IBTrACS dataset, provided by NOAA, includes the spatial and temporal distribution of tropical cyclones worldwide. It is one of the most complete global sets of historical tropical cyclones available. We make use of the reported timing – every 6 hours, and the extent of hurricanes. The list of the U.S. Hurricanes that are included in our sample is summarized in Table A.1. Over our sample periods, 33 hurricanes occurred and all of them happened during a hurricane season, between July to November. The intensity and the wind speed of the tropical cyclones vary across hurricanes. We match the date of hurricanes (Column
(1)) to the closest Election Day date (Column (9)) and calculate how many days are left until the next general election when the hurricanes hit. We define a hurricane as an ‘on (off)-cycle’ hurricane if the next election set less (more) than 365 days after the hurricane hits.

To extract local wind speeds, we use the CLIMADA wind field model, supported by the University of Zürich. The algorithm essentially computes the 1-min sustained peak gusts in each cell of a gridded map as the sum of a circular wind field (Holland, 2008) and the translational wind speed that arises from the storm movement (Aznar-Siguan and Bresch, 2019). We bring the IBTrACS hurricane data to this model and define a grid cell resolution of .12 degrees (approximately 12 km).

**Surveillance Epidemiology and End Results (SEER) database** — The Surveillance Epidemiology and End Results (SEER) population database provides detailed population counts by age, gender, and race, since 1969. This database, already used by Deryugina (2017), provides useful, clean, and consistent intercensal estimates. The original population source is taken from the Census.

**Bureau of Economic Analysis (BEA)** — The Bureau of Economic Analysis stores useful county-level information spanning back from at least 2001 (and up to 1969) to nowadays. We collect information on GDP, employment, personal wages and incomes, and non-disaster transfers (e.g., Medicare, unemployment benefits, etc.). When available, we also download this information by NAICS industry or other source’s type. Combined, this data provides detailed and clear information on the counties’ labor market and production profiles between 2001 and 2019.

**The Government Finance Database** — The Government Finance Database (Pierson et al., 2015) collects, cleans, and classifies in a standard way the information provided by the Census of Governments. We compile local public finance information for spending and revenue categories, aggregated at the county level. Because this information is only available every five years (years ending with ‘2’ or ‘7’), we infer intercensal data points from the corresponding yearly series available at the state level at the Tax Policy Center.
Table 2: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observation</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Population</td>
<td>3,079</td>
<td>10.226</td>
<td>1.421</td>
<td>4.205</td>
<td>16.08</td>
</tr>
<tr>
<td>White population</td>
<td>3,079</td>
<td>10.072</td>
<td>1.421</td>
<td>4.205</td>
<td>15.791</td>
</tr>
<tr>
<td>Black Population</td>
<td>3,079</td>
<td>6.413</td>
<td>2.756</td>
<td>0</td>
<td>14.172</td>
</tr>
<tr>
<td>Youth (&lt;15y)</td>
<td>3,079</td>
<td>8.71</td>
<td>1.44</td>
<td>2.485</td>
<td>14.69</td>
</tr>
<tr>
<td>Retired (&gt;65)</td>
<td>3,079</td>
<td>8.276</td>
<td>1.329</td>
<td>2.485</td>
<td>13.755</td>
</tr>
<tr>
<td>Total Transfers</td>
<td>3,110</td>
<td>18.615</td>
<td>1.397</td>
<td>12.393</td>
<td>24.441</td>
</tr>
<tr>
<td>Social Security Benefits</td>
<td>3,110</td>
<td>17.653</td>
<td>1.377</td>
<td>11.945</td>
<td>22.993</td>
</tr>
<tr>
<td>Medical Benefits</td>
<td>3,110</td>
<td>17.648</td>
<td>1.423</td>
<td>10.84</td>
<td>23.658</td>
</tr>
<tr>
<td>Supplemental Income</td>
<td>3,110</td>
<td>14.695</td>
<td>1.66</td>
<td>0</td>
<td>21.564</td>
</tr>
<tr>
<td>Food stamps</td>
<td>3,110</td>
<td>14.125</td>
<td>1.656</td>
<td>0</td>
<td>20.32</td>
</tr>
<tr>
<td>GDP</td>
<td>3,110</td>
<td>20.3</td>
<td>1.601</td>
<td>15.461</td>
<td>26.695</td>
</tr>
<tr>
<td>GDP Private sector</td>
<td>3,110</td>
<td>20.115</td>
<td>1.629</td>
<td>15.174</td>
<td>26.58</td>
</tr>
<tr>
<td>GDP Public sector</td>
<td>3,110</td>
<td>18.372</td>
<td>1.55</td>
<td>13.31</td>
<td>24.476</td>
</tr>
<tr>
<td>GDP Private goods</td>
<td>2,686</td>
<td>18.882</td>
<td>1.579</td>
<td>12.785</td>
<td>24.774</td>
</tr>
<tr>
<td>GDP Private services</td>
<td>2,686</td>
<td>19.473</td>
<td>1.693</td>
<td>14.924</td>
<td>26.4</td>
</tr>
<tr>
<td>Personal Income</td>
<td>3,110</td>
<td>20.344</td>
<td>1.521</td>
<td>14.928</td>
<td>26.419</td>
</tr>
<tr>
<td>Total Employees</td>
<td>3,110</td>
<td>9.533</td>
<td>1.476</td>
<td>4.394</td>
<td>15.503</td>
</tr>
<tr>
<td>Total Establishments</td>
<td>3,081</td>
<td>6.434</td>
<td>1.461</td>
<td>.693</td>
<td>12.337</td>
</tr>
<tr>
<td>Unemployment (%)</td>
<td>3,087</td>
<td>5.065</td>
<td>1.836</td>
<td>1.7</td>
<td>17.6</td>
</tr>
<tr>
<td>Median housing value</td>
<td>1,081</td>
<td>11.59</td>
<td>.512</td>
<td>10.293</td>
<td>13.607</td>
</tr>
</tbody>
</table>

Notes: The Summary Statistics are based on the 2001 County level. All figures are in logs, unless specified otherwise.

Miscellaneous Sources — We further collect and aggregate at the county level information from different secondary sources, including FEMA post-disaster grants and Presidential Disaster Declarations freely accessible on the FEMA webpage, and the Zillow Housing Value Index (ZHVI), and electoral data, collected at the county and state levels from the MIT Election Lab.

4.2 Defining the Treatment

In our preferred specification, we define counties hit by hurricanes as counties that lie within a hurricane’s radius of maximum winds. This definition presents the advantage of only considering the same 6-hour (maximum) winds within a hurricane. Nonetheless, these wind intensities might not be comparable across different categories of hurricanes (i.e., two counties hit at the same time by different hurricanes might be differently affected). Later on, we document that our results remain unaffected when defining treated areas as hit by major hurricane winds (i.e., ≥ 50 m/s). This second definition has the advantage of
considering specific wind categories (i.e., category 3 and above) based on a hurricane’s absolute wind field distribution. However, wind velocities within a hurricane might not be similar (i.e., two counties hit at the same time by the same hurricane might be differently affected). In both cases, whether the threshold is defined by the hurricanes’ radius of maximum winds or the ad-hoc Saffir–Simpson expression of a major hurricane, we will present results controlling for local wind speeds and show the results remain qualitatively robust to alternative specifications.

Having defined areas hit by hurricanes, note that the regular hurricane season lasts from June to November in the North Atlantic basin, but most hurricanes occur during the Fall. This timing, which takes its roots in the Tropics’ weather conditions, is arguably orthogonal to general elections’ day that the Congress set, in 1845, on the first Tuesday of November to allow farmers to travel to the polling station after the Fall harvest.

Between 2001 and 2019, a total number of 33 hurricanes hit the U.S. Atlantic coast. Seventeen of them occurred less than 365 days before a general election (on-cycle disaster), and 16 happened more than 365 days before (off-cycle disaster). On average, a cyclone in our sample occurred 268 days before a general election. However, this number varies greatly due to the timing specific to the hurricane season. In our sample, 51.5% of the hurricanes occurred less than 365 days before a general election (on-cycle) and nearly half of the counties ever hit were hit by an on-cycle hurricane. Importantly, the average wind speed during on-cycle hurricanes (90 mph) is not statistically different from the average wind speed during off-cycle hurricanes (94 mph). Similarly, the average air pressure during on-cycle hurricanes (966 mb) is not statistically different from the average air pressure during off-cycle hurricanes (963 mb).

The upper panel in Figure 1 shows the spatial distribution of on-cycle and off-cycle hurricanes in our sample. Here, the extent is defined by the radius of maximum winds. On-cycle and Off-cycle hurricanes are geographically dispersed. Appendix table A.1 provides detailed information about their timing and extent. Table A.2 displays some basic land, demographic and economic characteristics of counties ever hit by a hurricane between 2001 and 1969. The summary statistics are for the year 2000 – i.e., the year before our main period of analysis. One can see that counties characteristics do not differ significantly between counties ever hit by off-cycle hurricanes and counties ever hit by on-cycle hurricanes associated with these values is typically 9 to 12 feet high and 50 to 100 miles wide. See https://bit.ly/2W8LlJi.
Figure 1: On-cycle vs. Off-cycle Hurricanes’ Spatial Distribution and Winds Extents

Notes: (i) The top panel displays the radius of maximum winds of all hurricanes having made landfall in the U.S. between 2001 and 2019 using IBTrACS hurricane data (ii) The bottom panel displays the wind distribution of both hurricanes Sandy and Katrina according to the CLIMADA wind field model using IBTrACS hurricane data (iii) Saffir-Simpson wind intensities: tropical storms (18-32 m/s), minor hurricanes (categories 1 and 2; 32-50 m/s), major hurricanes (categories 3-5; ≥50).
hurricanes. The bottom map in Figure 1 shows how the CLIMADA wind field model applies to two of the most famous on- and off-cycle hurricanes of our sample period – Sandy and Katrina, respectively. The map displays how the absolute wind intensities diffuse in space. We later use this information to control for local wind intensities and distinguish hurricanes’ impacts by wind category.

5 Empirical Evidence

In this part of the paper, we document several novel facts about the impact of natural disasters on the local economy. First, we provide causal evidence that the electoral cycle affects post-disaster efforts received by a county. In particular, on-cycle hurricanes increase the size of the channeled post-disaster funds to the affected region. We then document how this consequence of disaster timing diffuses in the spatial economy through population sorting.

5.1 Event-Study Analysis

Hurricanes are rare, heterogeneous, staggered events by definition. The difference-in-difference literature has recently pointed at potential massive threats to identification when treatment timing varies across units and periods. Building on Abadie (2005)’s work on non-staggered treatments, Goodman-Bacon (2021) first demonstrated that panel fixed effect estimators are biased with treatment roll-out. In particular, the classical two-way fixed effect estimator is a ‘weighted average of all possible two-group/two-period DiD estimators in the data.’ With treatment roll-out, these weights can be negative because already-treated units act as controls, at the very least harming identification and potentially leading to average treatment effects or average treatment on the treated of opposite sign. Since research highlighted these challenges, many papers proposed alternative estimators (Borusyak and Jaravel, 2017; De Chaisemartin and d’Haultfoeuille, 2020; Callaway and Sant’Anna, 2020; Sun and Abraham, 2020; Goodman-Bacon, 2021) and diagnostics to estimate potential bias. A short diagnostic test (using the command twowayfeweights from De Chaisemartin and d’Haultfoeuille (2020)) indicates little if any negative weights with our hurricane treatments alone or specifically for on-cycle

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12See Baker et al. (2021) for a summary.
or off-cycle hurricanes. Later, we strengthen this point by implementing Callaway and Sant'Anna (2020)'s estimator and testing our results against alternative methods.

Our preferred comparison group only includes locations that were hit by hurricanes during the sample period (2001-2019). That is to say, we are comparing regions hit by on-cycle (off-cycle) hurricanes to regions not yet hit by an on-cycle (off-cycle) hurricane. We do so because we believe it makes the comparison more intuitive, as the potential exposure to the disaster does not vary between these two groups. However, still following Callaway and Sant’Anna (2020), we also use never-treated counties (i.e., counties that were never hit neither by an on-cycle nor by an off-cycle hurricane) as the control group for robustness.

Some areas in our sample experienced more than one hurricane during this period; others experienced a hurricane before or after. We only use the first hurricane occurrence in any given region for the estimation (i.e., the treatment is ‘absorbing’). In other words, we filter out cyclones that occurred before 2001 or after 2019, as well as any hurricane that occurred between 2001 and 2019 in a location that had previously experienced such a disaster during that period. In doing so, we focus on the impact of having ever received the treatment during our sample period and capture the path of treatment effects, even though the treatment itself may be transient (Sun and Abraham, 2020).

Additionally, we make the reasonable assumption that conditional on the county and year-fixed effects, the occurrence, and path of a hurricane is as good as random. A fortiori, the occurrence of a hurricane in a given place, at a specific time distance from the next general election, is as good as random. Note that these assumptions may not be sufficient to ensure identification of the ATE, given the staggered nature of our treatment. This is why, as mentioned above, we implement the method developed by Callaway and Sant’Anna (2020).

We use a simple event study design to estimate the dynamic effects of both ‘on-cycle’ and ‘off-cycle’ hurricanes. Our main specification reads:

\[ Y_{it} = \alpha_i + \gamma t + \sum_{l} \mu_l 1\{t - E_i = l\} + \epsilon_{it} \]  

where \( Y_{it} \) is the (log of the) outcome of interest in county \( i \) at year \( t \); 1 is an indicator for having ever been hit by an on- or off-cycle hurricane, and \( E_i \) is the year of the first
on- or off-cycle hurricane experienced in county $i$ in the sample period. County fixed effects ($\alpha_i$) and year fixed effects ($\gamma_t$) are included in the regression as well, and standard errors are clustered at the county level. Following Callaway and Sant’Anna (2020), in pre-treatment years the base year is the immediately preceding year. Later, we show that our results remain quantitatively and statistically similar when controlling for the hurricane’s intensity upon landfall, using larger sample periods and alternative estimators.

### 5.1.1 Local Public Finance

First, we investigate whether the timing of hurricanes relative to Election Day serves as a good predictor of post-disaster efforts. To give the flavor of public administration’s response at the local level, we start regressing the log difference between local expenditures and local taxes aggregated at the county level between 2001 and 2019. To generate our sample, we collect county-aggregated data on total taxes and total expenditures from the Government Finance Database (Pierson et al., 2015) – available every five years – and interpolate the intercensal years on the corresponding yearly aggregated State and local series from the State and Local Finance Database of the Tax Policy Center. We do not perform further interpolation on any public finance subcategories, as these might remain insufficiently documented with such local data. Figure 2 presents the dynamic effects of hurricanes on local expenditures and tax collection at the county level.

Our results confirm what previous literature has found – when pressured by electoral incentives, governments exert more post-disaster efforts. We see that aggregated expenditures at the local level rose faster than collected taxes after an on-cycle hurricane – but not after an off-cycle one, indicating that governments’ budgetary efforts depend on disaster timing. Over the post-treatment period, expenditures grew on average 2% faster than taxes, with a 4.5% increase after ten years. This effect is driven in the short run by increasing expenses and in the longer run by falling tax revenues. This is in line with Jerch et al. (2020) who also find that overall, large hurricanes increase local budgets’ deficits by reducing expenditures and tax revenues, but we find that these effects are entirely driven by on-cycle hurricanes. We therefore interpret the differences in reaction to on- and off-cycle hurricanes as evidence that local governments hit close to an election receive

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Note that using a fixed, universal base period or a varying-base period is just a linear combination of the other, so ‘they essentially are just alternative ways of reporting the same information.’ – see [https://bcallaway11.github.io/posts/event-study-universal-v-varying-base-period](https://bcallaway11.github.io/posts/event-study-universal-v-varying-base-period) for an intuitive explanation.
larger assistance from higher governmental layers – and in particular, from the federal government, whose responses to the disaster are being monitored by voters.

The impact of on-cycle hurricanes on immediate post-disaster FEMA grants supports this claim. In section A.2 of the appendix, we document such federal assistance can be as twice as large when an on-cycle hurricane hits a county compared to an off-cycle one. In line with our former results, the impact of hurricane timing on post-disaster grants appears to be particularly strong when grants are earmarked for local administration and not to private individuals. Large disasters further drive this effect, echoing the fact that the Disaster Relief Fund primarily reacts to catastrophic events.

Figure 2: On-cycle vs. Off-cycle Hurricane Treatment Effect on Local Expenditures and Tax Revenues

Notes: This figure plots event study estimates and corresponding 95 percent confidence bands of different specifications of equation (1). The dependent variable in the upper panel is the difference between log expenditures and taxes collected at the local level. Event variables are dummies equal to 1 for a hurricane. The estimation sample comprises all treated and not-yet-treated counties. The regression model includes county and year fixed effects. Standard errors are clustered at the county level.
Overall, these results are consistent with what previous literature has found that governments’ bailout activities are more responsive where the electoral accountability is greater (Besley and Burgess, 2002; Strömberg, 2004). The combination of highly destructive events and upcoming elections is also likely to generate media attention, superimposing an echo chamber to the local devastation and further pressuring incumbent national politicians. Previous studies also show that governments appear to be more generous with disaster relief during election years, which can lead to suboptimal policy outcomes (Cole et al., 2012).

Our empirical results generally show that post-disaster efforts are unevenly distributed across spaces with similar disaster risks but different electoral incentives. Excessive post-disaster efforts in locations that an on-cycle hurricane has hit may deter economic activity from adapting by moving away from high disaster risk locations. In the next part of our empirical analysis, we will document the impact of this inconsistency on the economy and, in particular, on population sorting.

5.1.2 Population and Demographic Sorting

Given that there is little consensus among researchers on what the dynamic impacts of natural disasters are for local economic outcomes (Botzen et al., 2019), our next empirical results are surprising but intuitive. Areas affected by natural disasters can reconstruct and revitalize the local economy through increased government’s support. This aid encourages the sorting of individuals in the affected areas.

Figure 3 presents the overall dynamic population response to a hurricane, depending on whether the disaster occurred close (i.e., on-cycle) or far (i.e., off-cycle) from Election Day. Both graphs document a sharp and significant positive population response when hurricanes occur close to Election day and trigger greater post-disaster efforts. In particular, the population has grown by 4.6% seven years after an on-cycle hurricane and 10.4% after 13 years compared to counties that an on-cycle hurricane has not yet hit. The average treatment effect of on-cycle hurricanes on population is about 4.7%. This effect is almost immediate: the population starts to grow in the second year after the natural disaster, consistent with the idea that infrastructure repairs and public good provisions are not immediate. Finally, this effect is persistent in the long run: we do not observe a reversal to pre-treatment population growth rates before at least 15 years. In contrast,
counties hit by off-cycle hurricanes do not display any population response. Growth rates with respect to the reference period do not change significantly compared to counties that an off-cycle hurricane has not yet hit. Finally, both on-cycle and off-cycle population dynamics are significantly different from one another.

Exploring heterogeneous demographic dimensions illustrates this general pattern. For instance, the population sorting is characterized by a permanently increasing ratio of white vs. non-white people in both the on-cycle and the off-cycle cases (Figure A.2). This ratio grows faster in the off-cycle case: it has increased by 10.2% only three years after the disaster in the off-cycle case, while it takes twice that time to reach similar levels in the on-cycle case. Given that the population did not grow faster in counties hit by off-cycle hurricanes during that period (Figure 3), this indicates that the non-white population tended to leave counties affected by off-cycle hurricanes and be replaced by white newcomers. Therefore, the different population sorting patterns documented so far seem accompanied by sorting on race, possibly linked to a local gentrification phenomenon. This
possibility is supported by further evidence at the industry level: the industries which experienced the clearest GDP boom after an on-cycle hurricane belonged to the government, the food and accommodation sector, the construction, and the financial services sectors (see Appendix section A.4). Additionally, housing prices seem to react positively to an on-cycle hurricane, whereas they seem to decrease as the result of an off-cycle one (see Appendix section A.5). Finally, Figure A.3 documents that the ratio between the population in the labor force (here, approximated by the population older than 16 and younger than 65) and the population out of the labor force increases faster in the on-cycle case while it remains similar to pre-treatment levels for at least a decade in the off-cycle disaster scenario. This latter effect may indicate that the local labor supply increases as a result of the post-disaster stimulating policies.

5.2 Mechanisms

To ensure that population sorting is indeed affected by electoral incentives and not some concurrent non-electoral mechanism, we explore the treatment effects along alternative political dimensions. We categorize the counties into politically aligned counties with the federal government in federal elections versus unaligned counties (Figure A.5, upper left); counties who voted for democrats versus republicans in federal elections (Figure A.5, upper right); and counties belonging to a swing state versus a non-swing state (Figure A.5, bottom). The results show that after hurricanes, politically aligned counties, republican counties, and counties in swing states are likely to experiment population sorting. Respectively, politically unaligned counties, democrat counties, and counties in non-swing states do not experience the population sorting phenomenon described earlier. Note that these political dimensions cannot be treated as exogenous as the timing of hurricanes relative to Election Day, but they support our hypothesis that political incentives shape post-disaster reaction and the subsequent sorting patterns.

The question is then to understand whether this sorting pattern is generated by an increased inflow of population or by an increased number of people remaining in affected areas. To better understand the spatial sorting pattern, we split the population stock into flows of stayers, migrants moving in (inflow), and migrants moving out (outflow). To do so, we make use of the IRS county-to-county migration data, which tracks the number of exemptions filed by taxpayers at the county level. While the number of exemptions is
not population per se, and exemption status might be a function of post-disaster efforts, it is a good proxy 'which approximates the number of individuals'. Figure A.6 shows the dynamics of population flows in response to hurricanes for counties hit by on-cycle hurricanes (left) and off-cycle hurricanes (right). When one regresses each flow separately against our treatment, it turns out that the increase in population after on-cycle hurricanes does not seem to come from more people moving to the affected areas but seems to follow an increasing number of people deciding to stay. Note, however, that while these figures give the flavors behind the population sorting pattern, we cannot provide a strict interpretation due to the inherent IRS data limitations.

5.3 Discussion

We now explore the internal and external validity of our main results. First, our results appear to be robust to alternative estimators. Figure A.7 of Section A.8 documents that the main population response remains qualitatively similar when applying Borusyak and Jaravel (2017)’s, Sun and Abraham (2020)’s, or the traditional OLS estimators. Similarly, Figure A.8 shows that the population sorting result also remains essentially unchanged when using counties never hit by a hurricane in our sample period as a comparison group and/or controlling for wind velocity upon landfall. Additionally, we check that our main result is not the product of recent extreme weather events by extending our analysis period to 1969. Figure A.9 documents that population increases dramatically in counties hit by on-cycle hurricanes, even before the 2000s. Figure A.10 shows that this effect is mostly driven by events having occurred after the 1988 Stafford Act, which gave the President increased discretionary power over post-disaster policies, which further reinforces the idea that federal electoral incentives play a major role. Exploiting the full wind field distribution, Figures A.11 and A.12 document that only major winds are likely to drive the sorting response, in line with the Disaster Relief Fund details. Finally, we check that our main result is not caused by a specific type of disaster (here, hurricanes) by using instead wildfires and floods as treatment. To do so, we first collect information on the 500 largest wildfires between 1988 (i.e., the year of the Stafford Act) and 2019 from the Interagency Fire Perimeter History dataset. Figure A.13 documents that population significantly increases as well in counties hit by on-cycle wildfires as opposed to off-cycle wildfires. We then collect information on the extreme flood events not caused by storms or hurricanes
over the same period from the Dartmouth Flood Observatory (DFO) (Kocornik-Mina et al., 2020). Again, Figure A.14 documents that the population significantly increases in counties hit by on-cycle floods as opposed to off-cycle floods. This is supportive of the idea that our main result is a general result that can be extended to other types of extreme events, and is not limited only to hurricanes.

Overall, we document that population, motivated by larger post-disaster transfers provided out of short-term electoral incentives, sort permanently in exposed areas. While this channel appears to us as the most straightforward and natural to explain the link between disaster timing and population sorting patterns, we cannot affirm that the post-disaster intergovernmental transfers medium is either the only or the most important channel. For instance, natural disasters occurring close to Election Day could affect other types of transfers, particularly non-disaster transfers (Deryugina, 2017) to individuals (e.g., Medicare, unemployment benefits, etc.). We exclude this one possibility by looking at how such transfers respond to off and on-cycle hurricanes (Section A.10 of the Appendix). Overall, counties hit by on-cycle disasters seem to receive decreased per capita non-disaster transfers from governments than counties not yet hit by similar disasters. This result is essentially caused by increased population sorting in areas hit by on-cycle disasters. Only unemployment benefits per capita increase after an on-cycle hurricane, which is also in line with our results. Non-disaster transfer growth from businesses and non-governmental organizations (e.g., charities) do not seem to be impacted by on-cycle hurricanes.

However, despite these results, we acknowledge that the increased post-disaster grants as a response to natural disasters coinciding with election cycles might not be the only channel that could potentially affect the population growth of the affected areas. In particular, changes in the regulatory framework may also influence how these transfers translate into local public services/amenities and, therefore, influence sorting patterns. We further discuss this point when assessing the impact of hurricanes on local amenity values in section 7.5. Generally, we understand the timing of hurricanes with respect to post-disaster grants as a good predictor of post-disaster efforts rather than specific post-disaster transfers.

Abstracting from the political economy channel we presented, our results document that hurricanes lead, on average, to sorting households into exposed areas. Recent studies also demonstrate these inefficiencies across the world. For instance, Tellman et al. (2021),
estimates the total population in locations with satellite-observed inundation grew by 58–86 million from 2000 to 2015. Magontier and Martinez-Mazza (2022) find that urban development increased and densified in Spanish municipalities hit by floods between 1979 and 2017. Using floods and night light information as in Kocornik-Mina et al. (2020) and applying Callaway and Sant’Anna (2020)’s method, we can see that massive floods, located around the equator, actually stimulated economic activity in the affected areas. Therefore, this general sorting pattern seems robust to different disasters and national contexts, seemingly indicating that (public or private) post-disaster intervention plays a significant role in adjusting economic activity.

6 A Dynamic Spatial Model with Post-Disaster Policies

How important is this sorting pattern for the aggregate economy? In this section, we build on our previous empirical findings. We aim to provide the simplest setup to analyze the role of post-disaster policies and electoral cycles in the spatial distribution of economic activity. Since heterogeneous impacts of natural disasters require different post-disaster policies across space, we introduce local public goods provision and intergovernmental transfers into a dynamic spatial equilibrium model. A dynamic framework is needed, since there are also important dynamic growth effects associated with changes in the spatial distribution of economic activity in response to post-disaster policies. In building our dynamic spatial model, we follow Desmet et al. (2018) and Desmet et al. (2021) but make two important amendments. First, similar to Henkel et al. (2021) governments in every region provide local public services (among other things, seawalls, etc.), and a fiscal transfer scheme reallocates resources across jurisdictions. Second, local governments receive intergovernmental grants and adjust their post-disaster efforts (i.e., the transformation rate of public spending into durable public goods and amenities valued by workers) depending on being hit by a disaster shock and the electoral cycle. We consider an economy consisting of $r \in S$ regions with total land density $\int_S H(r) dr = 1$. There is a mass $\bar{L}$ of homogeneous workers who are (imperfectly) mobile across regions. The initial population distribution is given by a continuous function $\bar{L}_0(r)$.

Preferences An infinitely lived representative household $i$ who resides in $r$ in period $t$ and who lived in locations $\bar{r}_- = (r_0, ..., r_{t-1})$ in the previous periods derives utility from
consumption of a private good $c_t(r)$ and public services $g_t(r)$ according to the following Cobb-Douglas preferences, where $0 < \gamma < 1$:

$$u^t_i(r, -), r) = \left[ \left( \frac{g_t(r)}{L_t(r)} \right)^\gamma \cdot c_t(r) \right]^{1-\gamma} \cdot a_t(r) e_t^i(r) \prod_{s=1}^{t} m(r_s, r_{s-1})^{-1}.$$  (2)

The parameter $\eta \in [0; 1]$ governs the degree of rivalry in public services, with $\eta = 0$ capturing the case of a pure local public good and $\eta = 1$ of fully rival per-capita transfers.

Agents discount the future at rate $\beta < 1$, and so the utility of a household $i$ in the first period is given by $\sum_t \beta^t u^t_i(r^t, r_{t-1})$, where $r^t$ denotes the location decision at $t$, $r_{t-1}$ denotes the history of locations before $t$, and $r^0$ is given.

The local amenity term $a_t(r) = \bar{a}_t(r) \bar{L}_t(r)^{-\lambda}$ contains a fundamental amenity term $(\bar{a}_t(r))$ which includes environmental amenities like warm weather, clean air and water, as well as the rate at which the government transforms public spending into utility valued by households (Similar to Fajgelbaum et al. (2019)), and an endogenous part that is negatively linked to population per unit of land at $r$ in period $t$ $(\bar{L}_t(r)^{-\lambda})$, where $\lambda \geq 0$ governs the strength of that endogenous dispersion force. Each locations’ fundamental amenity level is affected by local disasters through the function $\Lambda^a_t(r)$.

$$\bar{a}_t(r) = (1 + \Lambda^a_t(r) \cdot I_t(r)) \bar{a}_{t-1}(r).$$  (3)

The size of $\Lambda^a_t(r)$ depends on the local disaster probability and the electoral cycle and defines the percentage change of $\bar{a}_t(r)$ in response to a disaster. If a natural disaster hits a region $r$ at period $t$ $(I_t(r) = 1)$, the rate at which the local government transforms public funds into amenities valued by workers is changed by $\Lambda^a_t(r)$. When there is no disaster, the level of fundamental amenity remains constant and is given by $\bar{a}_t(r) = \bar{a}_{t-1}(r)$.

The fundamental amenities valued by workers varies across the electoral cycle. $\varphi_a$ represents the additional effect on the transformation rate during an on-cycle year, $I_t = 1$, compared to an off-cycle year $\bar{\lambda}_a$.

$$\Lambda^a_t(r) = (\bar{\lambda}_a + \varphi_a \cdot I_t).$$  (4)

Our specification also accounts for idiosyncratic location preferences $e_t^i(r)$ and moving costs $m(r_s, r_{s-1})$ from having resided in different places in the past. Idiosyncratic taste
shocks are assumed to be independent and identically distributed across households, locations, and time according to a Fréchet distribution with shape parameter $1/\Omega$ and scale parameter 1. A greater value of $\Omega$ implies more variety in agents’ tastes across locations, acting as an additional dispersion force. We follow Desmet et al. (2018) in simplifying the dynamic mobility decisions of the representative households to a sequence of static decisions.\footnote{We assume, that the mobility cost of moving from $r$ to $s$ is a function of an origin-specific cost term, $m_1(r)$, and a destination-specific cost term, $m_2(s)$. This means that $m(r, s) = m_1(r)m_2(s)$ with, $m(r, r) = 1$ for all $r, s \in S$, such that $m_2(r) = m_1(r)^{-1}$. The intuition is that the representative household only pays the permanent utility flow cost of moving to a specific location while residing there. Once it moves away, the household gets compensated by a permanent utility flow benefit, which is inverse proportional to the initial cost of moving there. In other words, migration decisions are reversible and, therefore, the location choice of households only depends on current variables and not on past or future ones.}

A household derives income from net-of-tax ($t_t(r)$) labor income $(1 - t_t(r))w_t(r)$, and from the local ownership of land $R_t(r)/L_t(r)$. Economic agents cannot write debt contracts with each other.

The number of households living at $r$ at time $t$ is given by:\footnote{See Desmet et al. (2018) for a complete derivation.}

$$H(r)L_t(r) = \frac{u_t(r)^{1/\Omega}m_2(r)^{-1/\Omega}}{\int_S u_t(v)^{1/\Omega}m_2(v)^{-1/\Omega}dv}L. \quad (5)$$

Production Technologies The specification of the production technology closely follows Desmet et al. (2018), where all its dynamic implications are developed and discussed. We add, however, the term $\Lambda^\tau_t(r)$, which incorporates the effect of natural disasters on local productivity. In every region, $r$, a continuum of firms produces a unique variety $\omega$ of a differentiated intermediate good under perfect competition using a constant-returns-to-scale technology in land and labor. Output per unit of land of variety, $\omega$, is given by

$$q_{\omega,t}(r) = \phi_{\omega,t}(r)^{\gamma_1}z_{\omega,t}(r)L_{\omega,t}(r)^{\mu}; \quad (6)$$

where $L_{\omega,t}(r)$ denotes the amount of labor per unit of land. Note that, since land is a fixed factor with share $1 - \mu$, agglomerating labor in a location yields decreasing returns, which acts as a congestion force.

Each firm’s productivity is determined by its innovation-decision, $\phi_{\omega,t}(r) \geq 1$, and an idiosyncratic location-variety-specific productivity shifter, $z_{\omega,t}(r)$. Firms can invest in innovation by employing $\nu\phi_{\omega,t}(r)^{\zeta}$ additional units of labor per unit of land, where $\zeta > \gamma_1/[1 - \mu]$. The location-variety-specific innovation-decision creates a local advantage
to scale and constitutes an agglomeration force, where the strength of this agglomeration force is increasing in the returns to innovation, as captured by $\gamma_1/\zeta$.

The exogenous productivity shifter is the realization of a random variable that is independent and identically distributed across varieties and time according to a Fréchet distribution with cumulative distribution function $F(z,r) = e^{-T_t(r)z^{-\theta}}$. The scale parameter $T_t(r)$ governs the level of productivity in a location and is affected by agglomeration externalities as a consequence of high population density and endogenous past innovations. The shape parameter $\theta > 0$ governs the dispersion in productivity draws across locations. We let $T_t(r) = \tau_t(r)\bar{L}_t(r)^{\alpha}$, where $\tau_t(r)$ represents a location-specific productivity term, and the positive impact of $\bar{L}_t(r)$ on $T_t(r)$ captures additional agglomeration economies such as knowledge spillovers. A greater dispersion in draws across locations increases the effect of population density on average productivity, such that the strength of this agglomeration force is increasing in $\alpha/\theta$.

In turn, fundamental productivity, $\tau_t(r)$, is determined by the impact of local disasters and an endogenous dynamic process given by

$$\tau_t(r) = (1 + \Lambda_t^* \cdot 1_t(r)) \left( \phi_{t-1}(r)^{\theta_1} \left[ \int_{S} \eta(r,s)\tau_{t-1}(s)ds \right]^{1-\gamma_2} \tau_{t-1}(r)^{\gamma_2} \right). \quad (7)$$

Each location’s fundamental productivity term is directly affected by local disasters through the impact function $\Lambda_t^*(r)$, with $1_t(r) = 1$ if a natural disaster hits a region $r$ at period $t$ and zero otherwise. The term $\phi_{t-1}(r)^{\theta_1}$ represents the shift in the local distribution of shocks that results from the last periods’ innovation decisions of firms, which are assumed to now constitute the local technology. The individual contemporaneous effect of innovation affects the production function in (6) directly. The term $\left[ \int_{S} \eta(r,s)\tau_{t-1}(s)ds \right]^{1-\gamma_2} \tau_{t-1}(r)^{\gamma_2}$ denotes the level of past productivity that firms build on, with $\int_{S} \eta(r,s) = 1$. It is composed of the location’s productivity level $\tau_{t-1}(r)$, as well as technology diffusion from other locations, where the function $\eta(r,s)$ denotes the spatial decay in the strength of technology diffusion. Note that $\eta(r,s)$ also governs the spatial distribution of productivity shocks in response to natural disasters. That is, the dynamic evolution of a location’s technology level is not only shifted up by past innovations but also affected by the impact of natural disasters in all other locations if $\gamma_2 < 1$.

Land markets are competitive. A continuum of potential entrants competes in prices
(à la Bertrand), i.e., all firms bid for land to enter the market. Since there is a continuum of potential entrants, all firms bid until the winning firm makes zero profits net of the fixed innovation costs. Hence, the solution to the dynamic innovation problem of firms in this economy is to choose the level of innovation that maximizes their current profits (or, equivalently, their bid for land) every period. Future firms’ profits are zero because all future gains of today’s innovations will accrue to the fixed factor land reflected by the local land price, $R_t(r)$. The firms’ innovation decisions remain, therefore, unaffected by the effect of future productivity gains of current innovations via (7). Again, this implies that the firm’s optimization problem reduces simply to a static problem. In sum, individual firms in location $r$ take input costs as given and maximize current profits per unit of land by choosing the amount of labor per unit of land for production and innovation,

$$
\max_{L_{\omega,t}(r), \phi_{\omega,t}(r)} p_{\omega,t}(r,r)\phi_{\omega,t}(r)L_{\omega,t}(r)^\mu - w_t(r)L_{\omega,t}(r) - w_t(r)\nu\phi_{\omega,t}(r)^\xi - R_t(r), \quad (8)
$$

where $p_{\omega,t}(r,r)$ is the price charged by the firm of a good sold at $r$.$^{16}$

**Prices and Export Shares** Intermediate goods markets are competitive, so firms sell goods at marginal cost after accounting for transport costs.

Let $\zeta(s, r) \geq 1$ denote the iceberg trade cost of transporting a good from $r$ to $s$. Then, the price of an intermediate good $\omega$ produced in $r$ and sold at $s$, is given by

$$
p_{\omega,t}(s, r) = \frac{\zeta(s, r)mc_t(r)}{z_{\omega,t}(r)}, \quad (9)
$$

where $mc_t(r) \equiv [1/\mu][\nu/\gamma_1]^{1-\mu}[\gamma_1 R_t(r)/w_t(r)\nu(\zeta(1 - \mu) - \gamma_1)]^{(1-\mu)-(\gamma_1/\zeta)}w_t(r)$ denotes the marginal input cost at location $r$.

The probability density that an intermediate good produced in $r$ is bought in $s$ is given by

$$
\pi_t(s, r) = \frac{T_t(r)[mc_t(r)\zeta(r, s)]^{-\theta}}{\int_S T_t(u)[mc_t(u)\zeta(u, s)]^{-\theta} du} \quad \text{for all } r, s \in S. \quad (10)
$$

A final good $Q_t(r)$ is assembled from the continuum of intermediates according to the following CES aggregator:

$$
Q_t(r) = \left[ \int_S q_t(r, s)^{\rho} dr \right]^\frac{1}{\rho}. \quad (11)
$$

$^{16}$See Desmet et al. (2018) for a complete formal depiction of the optimization problem. In what follows, we rely on their formal derivations.
Here, \( q_t(r,s) \) denotes the quantity of the variety produced in location \( r \) and used for assembly in location \( s \), and \( 1/[1 - \rho] \) represents the elasticity of substitution between intermediates with \( 0 < \rho < 1 \). Final goods are not traded across regions, and assembly has no extra costs. This final good \( Q_t(r) \) can either be used directly for private consumption \( c_t(r) \), or by local governments to provide public services \( g_t(r) \). Thus, we have \( Q_t(r) = H(r)\bar{L}_t(r)c_t(r) + g_t(r) \).

The price of the final good in location \( s \) at time \( t \) is, therefore, given by the average price of the different goods that are being assembled in \( r \):

\[
P_t(s) = \bar{p}\chi_t(s)^{-\frac{1}{\rho}},
\]

with \( \chi_t(s) = \int S T_t(u) [mc_t(u)\zeta(u,s)]^{-\theta} du \) and \( \bar{p} = \left[ \Gamma \left( \frac{-\rho}{(1-\rho)\theta} + 1 \right) \right]^{-\frac{1-\rho}{\rho}} \).

**Government** In describing the public sector in this economy, we closely follow Henkel et al. (2021). Labor income is taxed at rate \( t_t(r) \), which generates an overall tax revenue equal to \( t_t(r)w_t(r)H(r)\bar{L}_t(r) \) in region \( r \) at time \( t \). The Federal government budget constraint is thus given by \( \int S t_t(s)w_t(s)H(s)\bar{L}_t(s)ds \). In every period \( t \), the Federal government redistributes overall tax revenues to local governments at rate \( \theta_t(r) \) across regions, where the transfer rate relative to local aggregate labor income is positive \( \theta_t(r) > 0 \) for recipient and negative \( \theta_t(r) < 0 \) for donor regions.

We keep the specification of the public sector as simple as possible. Though, it is flexible enough for our purpose of taking the model to the data. A few comments are in order about our setup. First, we assume that the government can commit to a tax policy sequence at time zero and cannot issue bonds to borrow money from the future. Second, our model abstracts from horizontal tax competition and national public goods. Note, however, that any national public good provided by the federal government is implicitly captured by the amenity term consumed by households. Third, we abstract from progressive tax schedules and dead-weight losses of income taxation. However, although households supply labor inelastically, we will see later that they respond to regional differences in tax and transfer rates through migration. Local governments, therefore, do face a mobile tax base, as households choose their locations endogenously.
Post-Disaster Policy and the Electoral Cycle Motivated by the empirical findings of the previous section, we introduce a relationship between fiscal transfers and natural disasters in our spatial general equilibrium model.

Letting $\theta_t(r)$ denote the transfer rate, the response of the federal government to natural disasters in setting local transfer rates reads as follows:

$$\theta_t(r) = \left(1 + \Lambda^\theta_t(r) \cdot 1_t(r)\right) \theta_{t-1}(r).$$  \hfill (13)

A natural disaster in a region $r$ raises its weight for the Federal government in channeling public funds to this particular region. If a natural disaster hits a region $r$ at period $t$ $1_t(r) = 1$ the previous periods level of the transfer rate $\theta_{t-1}(r)$ is adjusted by the Federal government by $\Lambda^\theta_t(r)$. More importantly, the electoral cycle affects the decision of the Federal government.

$$\Lambda^\theta_t(r) = (\bar{\lambda}_\theta^r + \varphi_\theta \cdot I_t).$$  \hfill (14)

When the disaster occurs within an election year, $I_t = 1$, the transfer rates increase more than during an off-cycle year. $\varphi_\theta > 0$ governs the size of this political cycle effect.

The local governments use the available public funds to provide a sequence of local public services $g_t(r)$. When there is no political cycle effect for the transfers, the level of local public goods is given by $g_t(r) = [t_t(r) + (1 + \bar{\lambda}_\theta \cdot 1_t(r)) \theta_{t-1}(r)] w_t(r)H_t(r)\bar{L}_t(r)/P_t(r)$.

Given the political cycle effect, however, the effective budget that is available for local public goods provision in a region $r$ during an on-cycle year is thus given by

$$g_t(r) = [t_t(r) + (1 + (\bar{\lambda}_\theta + \varphi_\theta \cdot I_t) \cdot 1_t(r)) \theta_{t-1}(r)] w_t(r)H_t(r)\bar{L}_t(r)/P_t(r).$$  \hfill (15)

Competitive Equilibrium A dynamic competitive equilibrium in this economy is defined by the following conditions:

1. Labor market clearing.

$$\int_S H_t(r)\bar{L}_t(r)dr = \bar{L}$$  \hfill (16)

2. Land market clearing. Land is assigned to the highest bidder, such that for all $r \in S$,

$$R_t(r) = \left[\frac{\zeta - \mu^r \zeta - \gamma_1}{\mu^r \zeta + \gamma_1}\right] w_t(r)\bar{L}_t(r).$$  \hfill (17)
3. **Goods market clearing.** Total labor income in region \(r\), \(w_t(r)H(r)\bar{L}_t(r)\), must equal region \(r\)'s total sales to all locations \(s \in S\):

\[
w_t(r)H(r)\bar{L}_t(r) = \int_S X_t(s, r)ds \quad \text{for all} \quad r \in S,
\]

where \(X_t(s, r) = \pi_t(s, r)[(1 + \theta_t(s))w_t(s)H(s)\bar{L}_t(s)]ds\) includes government transfers across regions.\(^{17}\)

4. **Balanced public budget.** The total amount of transfers paid must equal the total amount received, such that,

\[
\int_S \theta_t(s)w_t(s)H(s)\bar{L}_t(s)ds = 0.
\]

Moreover, every local government spends its available budget entirely on local public goods, \([t_t(r) + \theta_t(r)]w_t(r)H(r)\bar{L}_t(r) = P_t(r)\bar{g}_t(r)\), as imposed above in (15).

5. **Spatial sorting.** Given migration costs and their idiosyncratic preferences, households choose where to live, so (5) holds for all \(r \in S\).

6. **Utility.** The utility associated with net real income and amenities in location \(r\) is given by

\[
u_t(r) = a_t(r)\left(\frac{(t_t(r) + \theta_t(r))w_t(r)H(r)\bar{L}_t(r)}{\bar{L}_t(r)\bar{P}_t(r)}\right)^\gamma \left(\frac{(1 - t_t(r))w_t(r) + R_t(r)}/\bar{P}_t(r)\right)^{1-\gamma}
\]

\[= \bar{a}_t(r)\bar{L}_t(r)^{-\lambda+\gamma(1-\eta)}H(r)\gamma w_t(r)\bar{P}_t(r)\Theta_t(r) \quad \text{for all} \quad r \in S,
\]

where, \(\Theta_t(r) \equiv \left[(t_t(r) + \theta_t(r))^\gamma \left(\frac{\kappa}{\mu + \gamma t_t(r)} - t_t(r)^{1-\gamma}\right)]\), the price index is given by (12), and land markets are in equilibrium.

7. **Dynamic evolution of technology, amenity levels, and transfer rates.** Technology evolves according to (7) and amenity according to (3), and transfer rates evolve according to (13) for all \(r \in S\).

---

\(^{17}\)Note that net government transfers imply trade imbalances in equilibrium. Total imports must equal local labor income plus total net transfers, so \((1 + \theta_t(r))w_t(r)H(r)\bar{L}_t(r) = \int_S X_t(r, s)ds\). Comparing this expression with (18), we observe that the difference between exports and imports is given by \(- (\theta_t(r))w_t(r)H(r)\bar{L}_t(r)\), while \(\int_S \theta_t(s)w_t(s)H(r)\bar{L}_t(r)ds = 0\).
Substituting utility (20), (12), and bilateral exports probabilities (10) into the goods-market clearing condition (18), we obtain

\[ w_t(r)^{1+\theta} H(r) L_t(r)^{1-\alpha+(1-\mu-\frac{\gamma_1}{\zeta})\theta} = \kappa_1 \int_S \zeta(r,s)^{-\theta} \tau_t(r) \left[ \frac{\bar{a}_t(s)}{u_t(s)} \right]^\theta \Theta(t(s))^{\theta}(1 + \theta_t(s)) \] (21)

\[ w_t(s)^{1+\theta} H(s) \bar{L}_t(s)^{1-(\lambda-\gamma(1-\eta))\theta} ds, \]

where

\[ \kappa_1 = \left[ \frac{\mu \zeta + \gamma_1}{\zeta} \right]^{-\left[ \frac{\mu-1+\frac{\gamma_1}{\zeta}}{\gamma_1} \right]} \mu^\theta \left[ \frac{\zeta \nu}{\gamma_1} \right]^{-\frac{\gamma_1}{\zeta}} \bar{p}^{-\theta}. \]

Second, combining (20) and (12) allows us to rewrite the price index equation as follows

\[ \bar{L}_t(r)^{-[\lambda-\gamma(1-\eta)]\theta} w_t(r)^{-\theta} = \kappa_1 H(r)^{\theta} \Theta_t(r)^{\theta} \left[ \frac{\bar{a}_t(r)}{u_t(r)} \right]^{\theta} \]

\[ \int_S \tau_t(s) \zeta(s,r)^{-\theta} w_t(s)^{-\theta} \bar{L}_t(s)^{\alpha-(1-\mu-\frac{\gamma_1}{\zeta})\theta} ds. \] (22)

Conditional on \( \tau_t(\cdot), \bar{a}_t(\cdot), \bar{L}_{t-1}(\cdot), \zeta(\cdot,\cdot), m(\cdot,\cdot), H(\cdot), t_t(\cdot), \theta_t(\cdot), \Lambda^\alpha_t(\cdot), \Lambda^\theta_t(\cdot) \) and given parameter values, the system (21) and (22) together with (20) could be solved for the equilibrium wages, population density, and utility for any \( t \) and for all \( r \in S \). While \( \tau_t(\cdot) \) comes directly from (7) and \( \bar{L}_{t-1}(\cdot), \bar{a}_t(\cdot) \) from (3), and \( \theta_t(\cdot) \) from (13).

In their model, Desmet et al. (2018) have shown that \( \lambda + (1 - \mu) + \Omega \geq \frac{\alpha}{\theta} + \frac{\gamma_1}{\zeta} \) is a sufficient condition to ensure the existence and uniqueness of a stable equilibrium, although equilibria may also exist if that condition is not satisfied. In our framework with local public goods and fiscal transfers, the respective sufficient condition reads as:

**Condition 1:** \[ \lambda + (1 - \mu) + \Omega \geq \frac{\alpha}{\theta} + \frac{\gamma_1}{\zeta} + \gamma(1-\eta). \]

In words, the static congestion forces parameterized by \( (\lambda; (1 - \mu); \Omega) \) are at least as strong as the sum of the static agglomeration forces \( (\alpha/\theta; \gamma_1/\zeta) \) and the sharing of public facilities \( (\gamma(1-\eta)) \). Notice that the net static agglomeration externality is then negative, \( \alpha/\theta + \gamma_1/\zeta + \gamma(1-\eta) - \lambda - (1 - \mu) - \Omega \leq 0 \), so that an inflow of population into region \( r \) reduces utility \( u_t(\cdot) \), ceteris paribus.

**Balanced Growth Path** The spatial distribution of employment is stable along a balanced growth path (BGP), and all areas grow at the same rate. Following the steps in Desmet et al. (2018), we can show that a balanced growth path exists if:
**Condition 2:**  \( \lambda + (1 - \mu) + \Omega \geq \frac{\beta}{\zeta} + \gamma (1 - \eta) + \gamma_1 / ([1 - \gamma_2] \zeta) \).

Intertemporal spillovers from previous innovations ensure that the economy does not stagnate in the long run. High-density places that have been innovative in the past are still productive locations nowadays. These areas then attract more labor and expand their market, making them ideal locations to innovate today. The influence of past productivity on the rest of the economy in establishing a location’s productivity guarantees that this dynamic agglomeration effect does not lead the economy to concentrate in one area over time. The supplementary term \( \gamma_1 / ([1 - \gamma_2] \zeta) \) represents this dynamic part of agglomeration economies.

7 Quantification: Post-Disaster Policies in the United States

To bring our model to the data, we consider the post-disaster policies in the United States described in Section 3. We quantify the model at the county level. Our baseline year is 2001. To quantify the model, we need values for all the economy-wide parameters, plus location-specific values for initial fundamental amenity and productivity levels, migration costs, and bilateral transport costs. We also need to estimate the impact functions on the level of amenities, productivities, and transfer rates.

7.1 Parameter choices and estimation

We choose baseline parameter values by relating to those in the existing literature and borrow the remaining parameter estimates from Desmet et al. (2018). Table 3 lists the parameters used in our model quantification.

7.2 Tax and transfer rates

To calculate local tax rates \( t_i(\cdot) \) and local transfer rates \( \theta_i(\cdot) \), we break down tax revenue and expenditure data from the Government Finance Database (Pierson et al., 2015) to the local level and relate them to these areas’ GDPs.\(^{18}\)

Figure 4 depicts the transfer rates ((expenditure - revenue)/GDP) of each U.S. county in 2001. It gets evident that most counties are neither net recipients nor net donors to the system of tax redistribution in the United States. It is worth mentioning, however, that in

\(^{18}\)Section B in the appendix provides a more detailed description of the data sources we use and our calculation steps.
<table>
<thead>
<tr>
<th>Preference</th>
<th>Parameter Values</th>
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<tr>
<td>$\beta = 0.965$</td>
<td>Discount factor for present values</td>
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<td>$\lambda = 0.32$</td>
<td>Amenity congestion w.r.t. local population</td>
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<td>$\psi = 1.8$</td>
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<td>Location taste heterogeneity parameter in Frechet distribution</td>
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<td>$\eta = 0$</td>
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<tr>
<td>$\zeta = 1$</td>
<td>Parameter driving scale of technology diffusion</td>
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<td>$\mu = 0.8$</td>
<td>Labor share in production, i.e. non-land share</td>
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<td>$\nu = 0.15$</td>
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<td>$\sigma = 4$</td>
<td>Elasticity of substitution</td>
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<td>Semi-elasticity of amenities w.r.t. disaster probability</td>
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<td>Impact of electoral cycle on transfer rate</td>
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<tr>
<td>$\varphi_a = 0.0381$</td>
<td>Impact of electoral cycle on amenities</td>
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<td>Estimated</td>
<td>Estimated</td>
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Desmet et al. (2018)
Desmet et al. (2018)
Desmet et al. (2018)
Monte et al. (2018)
Deaton and Stone (2013)
Cross-county mean of the counties’ tax revenue to GDP ratio
Desmet et al. (2018)
Desmet et al. (2018)
Desmet et al. (2018)
Appendix B.7 of Desmet et al. (2018)
Figure 4: Transfer rates in baseline year

Notes: This figure plots the transfer rates, \( \theta \), for our baseline parameter values and baseline year 2001. The warm colors indicate higher deciles transfer counties (i.e., recipients), and blue shadings are lower deciles transfer counties (i.e., donors).

In the United States, there is no specific scheme in place to equalize fiscal capacities across jurisdictions. Any differences between local expenditures and tax revenues come from tax policies or specific (mandatory, discretionary, and supplemental) spending programs of higher-order government layers. For example, the federal government collects more taxes from high-income than low-income states via the operation of the federal income tax but spends more on social security, Medicare, and other programs in low-income than high-income places. Hence, transfer rates are more likely to be negative (i.e., donating counties, closer to 1st decile in Figure 4) in high-income counties (in the Eastern Seaboard, Southern Florida, Southern California, Texas, and Arizona), while transfer rates are more likely to be positive (i.e., receiving counties, closer to 10th decile in Figure 4) in low-income counties (in the central United States, along the Appalachians, and in states like Oregon, Montana, and Nebraska).
7.3 Amenities and productivity

Next, we recover fundamental productivities \( \tau_t(r) \) and amenities combined with the rate of transformation of local public funds to the utility level \( \bar{a}_t(r) \) for every county from our general equilibrium model, given our parameter values, calculations for trade costs, and estimates for the damage function on amenities and productivities.

We plug in our calculations of trade costs \( \zeta(s, r) \), data on land \( H(r) \), tax rates \( t_t(r) \), transfer rates \( (\theta_C^C(r), \theta_G^C(r)) \), as well as population \( L_t(r) \) and wages \( w_t(r) \) for several periods of data into (21) and (22) to solve for \( \bar{a}_t(r)/u_t(r) \) and \( \tau_t(r) \). Finally, to disentangle the fundamental amenity \( \bar{a}_t(r) \) from the utility level \( u_t(r) \), we use a proxy, similar to the Human Development Index (HDI) as our measure of \( u_t(r) \). We follow Desmet et al. (2018) to transform it into a cardinal measure of well-being that is linear in log-real income.

Figure 5 plots the spatial distribution of amenities (Figure (a)) and productivities (Figure (b)). Figure (a) shows that the amenity level is higher in Florida, East Coast states, and a few counties in Southern California, Texas, and Washington. Figure (b) shows that the productivity is higher in counties located in California, Washington, and east coast counties and counties in the coastal areas of the Gulf Coast and Florida.

7.4 Migration Costs

Solving (5) for \( u_1(r) \) and plugging this into (21) and (22) we can use period 1 population \( \bar{L}_1(\cdot) \) and productivity levels \( \tau_1(\cdot) \) to solve for migration costs \( m_2(\cdot) \) up to scale. We use the productivity evolution equation (7) to obtain \( \tau_1(\cdot) \) from \( \tau_0(\cdot) \) and \( \bar{L}_0(\cdot) \), while we use data on the population distribution in 2006 to obtain \( \bar{L}_1(\cdot) \). We then normalize the level of migration costs such that its minimum value is equal to one.

7.5 Impact of Natural Disasters and Election Cycle

We identify the causal effect of natural disasters and the electoral cycle on amenities, productivities, and transfer rates using the following specification:

\[
y_t(r) = \alpha(r) + \gamma_t + (\Lambda_y + \varphi_y \cdot I_t) \cdot 1_t(r) + \epsilon_t(r),
\]

where \( y_t(r) \in \{\log \bar{a}_t(r), \log \tau(r) - \log \phi_t(r), \theta_t(r)\} \) are the logarithm of fundamental amenities, the logarithm of the ratio of fundamental productivities to innovations, and the level
Figure 5: ESTIMATED FUNDAMENTAL AMENITIES AND PRODUCTIVITIES

Notes: This figure plots the fundamental amenities combined with the rate of transformation (Figure (a)) and productivities (Figure (b)) for our baseline parameter values and baseline year 2001. The warm colors indicate higher deciles.
of transfer rates. \(1_t(r)\) is an indicator function for location \(r\) having been hit by a natural disaster in period \(t\). When the disaster occurs within an election year, \(I_t = 1\). We cluster standard errors at the county level. \(\alpha(r)\) and \(\gamma_t\) are location-specific and Congress area time invariant fixed effects, which ensures that identification of \(\bar{\lambda}_y\) and \(\varphi_y\) comes from variation in \(y_t(r)\) within, not across, counties. We then quantify the impact functions by

\[
\Lambda^y_t(r) = (\bar{\lambda}_y + \varphi_y \cdot I_t) \cdot 1_t(r).
\]

Our estimates in Table 3 and Figure B.3 show that amenities and local transfer rates increase after a natural disaster on average. The increases create additional incentives for individuals to move toward regions hit by a disaster. Moreover, this effect varies depending on the electoral cycle, with significantly higher impacts after on-cycle events. Please note, however, that the level of productivity does not change after a natural disaster.

**Discussion**  
In general, the amenity result comes from the fact that the amount of post-disaster grants understates the magnitude of resources provided in response to natural disasters. The reaction in fiscal capacities of local governments is not large enough to rationalize the assumption of a spatial equilibrium jointly with the population sorting pattern in the data. A few forces excluded from both our model and equation (23), however, may provide a rationale for the increasing local amenity values after natural disasters. Overall, we think about the changed amenity values as improvements in the quality of life brought about by redevelopment and investments in specific higher-quality public infrastructure, such as seawalls, water reservoirs, elevated roads, safe schools, or general safety, after being hit by a natural disaster. In other words, it could be that local communities supported by the federal government build higher-quality consumption amenities, infrastructure, and housing after being hit by a natural disaster. In this sense, higher post-disaster grants after on-cycle events only strengthen these effects.

Previous literature documents how important updating outdated housing stocks and infrastructures is for regional development. For example, *Hornbeck and Keniston (2017)* show that regional growth requires the replacement of obsolete buildings, and *Lee and Lin (2017)* document that older buildings are more prevalent in the coastal areas in the U.S. In this way, the higher public funds after natural disasters might trigger further redevelopment and updating building codes, which lead to more increased amenities. Additionally, households who have a strong preference to be in coastal areas are more likely
to be attracted to the improved amenities by the redevelopment, as they might care about specific amenities and act to preserve them through restrictive land-use zoning Kahn and Walsh (2015). Collective mitigation investments, such as road elevation or the conversion of floodplains in public parks, might foster these amenity improvements and encourage individuals to stay in exposed areas (McNamara and Keeler, 2013).

Secondly, the housing and mortgage market can play a role here. According to Ouazad and Kahn (2019), mortgage lenders are more likely to pass mortgages in vulnerable areas to government-sponsored enterprises (GSEs) in the aftermath of natural disasters. If this tendency is also associated with the local election cycle, that could also be a potential channel that can affect the spatial sorting of households. Another possible channel, which is associated with the local housing market, could be regulatory aspects. For example, since 2005, it has been possible to make statutory and regulatory appraisal requirements for certain property transactions. If more counties get declared during on-cycle years, this could imply more transactions on the property market and population growth in response to a hurricane.

Finally, the disaster events coinciding with political cycles could affect specific local public goods preferences. For example, voters might be more likely to vote for the local provision of public goods when a hurricane occurs close to an election. For now, in the model, we abstract from the aspect of changing preferences for local public goods, keeping the preference parameter for local public goods constant across our counterfactual simulations.

Although we acknowledge these possibilities, we leave the investigation of these alternative channels as our future work.

8 Counterfactual Analysis

Next, we evaluate the importance of the electoral cycle and post-disaster policies for the spatial distribution of economic activity and the aggregate economy. To do so, we run the following two counterfactual analyses:

— Counterfactual 1: Removing the Electoral Cycle
— Counterfactual 2: Removing Post-disaster Policies

19 See the rules and regulations of the Federal Register: https://www.govinfo.gov/content/pkg/FR-2005-10-14/pdf/05-20583.pdf.
We use synthetic hurricane paths for the following 80 years in the US, using the STORM dataset (Bloemendaal et al., 2020). Figure B.1 of the appendix shows examples of the distribution of on- and off-cycle hurricanes in this dataset. Again, storms appear to be geographically balanced. Note that the synthetic paths that we use in the current version of our counterfactual exercises mimic the current climate conditions, assuming no climate change in the future.

We use only an 80-year simulation period first because determining the far future fundamental amenity distribution requires understanding the long-run evolution of anthropogenic adaptation to climate change consequences. Making such an attempt is far beyond the scope of this paper, and not accounting for this critique would weaken the potential of our results. Second, it is unclear that the political and electoral institutions will remain as of today in the far future, and therefore electoral incentives will be unchanged. While difficult to amend, these are, of course, subject to constitutional changes.

Keeping these two reasons in mind, we maintain current climate conditions unchanged and avoid modeling climate change scenarios as determined by the various IPCC reports. This is because the evolution of both frequency and intensity of future major hurricanes is unlikely to change drastically before at least 50 to 100 years in the North-Atlantic basin and is still subject to discussion among meteorologists and climate scientists (Emanuel, 2011; Knutson et al., 2020). Of course, other disastrous consequences of climate change will emerge in the upcoming decades. However, major hurricanes will likely not change during our simulation 80-year period. Further, accounting for multiple disaster types would require a deep understanding to simulate how each hazard would dynamically evolve, at the local level, under several unified, hypothetical climate change scenarios. Beyond the technical challenge, we are not aware of any attempt made in the economic or climate science literature.

We start from the initial spatial equilibrium in the baseline year 2001 and simulate the model forward for 80 years using our historical and synthetic storm tracks. Following our empirical analysis, we use the radius of maximum winds to identify treated counties, as shown in Figure B.2 of the appendix. We compare our baseline scenario, which features post-disaster grants and amenity levels that vary across the Electoral cycle, with counterfactual scenarios.

---

Section B in the appendix provides a more detailed description of the data source. The data consists of more than 10,000 hurricane synthetic tracks predicted from the IBTrACS repository.
In our first counterfactual analysis, we remove the impact of the election cycle. To be more specific, we assume that the size of fiscal transfers and the level of amenities do not vary across the electoral cycle in response to natural disasters. Hence, we set \( \varphi_y = 0 \) and impose \( \Lambda^y_t(r) = (\bar{\lambda}_y) \cdot 1_t(r) \) for any \( t \) and for all \( r \in S \) in Equation 3 and Equation 13, where \( y \in \{ \bar{a}_t(r), \theta_t(r) \} \). In our second and most extreme counterfactual scenario, we shut down the impact of disasters on transfer rates, amenities, and productivities completely to assess the overall implications of post-disaster policies. To be more precise, we impose \( \Lambda^y_t(r) = 0 \) for any \( t \) and for all \( r \in S \) in Equation 3 and Equation 13, where \( y \in \{ \bar{a}_t(r), \theta_t(r) \} \).

In all of our counterfactual simulations, we assume fixed values of the exogenous parameters and the same local tax rates \( t_t(r) \) and trade costs \( \zeta(s, r) \) as in the initial equilibrium from the year 2001. Using the system (21) and (22) together with (20) we then solve for new (counterfactual) equilibrium wages, population density, and utility for any \( t \) and for all \( r \in S \). While we update \( \tau_t(\cdot) \) according to (7), \( a_t(\cdot) \) according to (3), and \( \theta_t(\cdot) \) according to (13).

### 8.1 Local Amenities and Public Goods Provision

We start the discussion of our results with the implied changes in the relative attractiveness of locations. Higher transfers and tax revenues allow for more public goods provision and thus make those regions relatively more attractive. In addition, our estimates in Section 7.5 have shown that the fundamental amenities increase after a natural disaster, which creates additional incentives for individuals to move toward these regions. Moreover, on-cycle events magnify the positive impact of a natural disaster.

Switching off the impact of the Electoral cycle on post-disaster grants, or removing the post-disaster policies completely, negatively affects government budgets and, therefore, local public goods provision across regions. Moreover, it influences the transformation rate of public funds into local amenity values. In our counterfactual scenarios, the level of local amenities and public goods provision does not increase in disaster-struck places anymore, contrary to our baseline. At the same time, public goods provision increases in the former donor regions, as they need to give less of their tax revenues to other counties (especially those hit by disasters).
8.2 Population Sorting

Henkel et al. (2021) show that fiscal transfers create incentives for households to move towards regions receiving transfers. Analogously, switching off the effect of the electoral cycle or abandoning post-disaster policies induces fewer people to stay in places hit by a natural disaster. Economic activity instead moves toward the former donor regions.

Figure 6 depicts ratios in local population size after 80 years in our baseline scenario, relative to our counterfactuals; switching off the effect of the Electoral cycle (panel (a)) and post-disaster policies completely (panel (b)). In our baseline, more households would stay in coastal areas with higher hurricane risks around the Gulf of Mexico, Southeast Florida, and the Atlantic Ocean. The current system of post-disaster policies increases the population in some coastal areas by up to 7 percent over the 80 years, relative to a scenario without post-disaster policies.

8.3 Real GDP and Productivity

The population sorting patterns accompanied by the current system of post-disaster policies relative to removing the Electoral cycle or the post-disaster policies lead to additional changes in productivity and real GDP across counties. In particular, the regions hit by the disasters which attract more population experience a boost in productivity via endogenous agglomeration economies and innovation in our baseline. The opposite happens in the donor regions, which experience outward migration, hence falling productivity and innovation. Since households move from relatively more to less productive/innovative areas, we observe a decline in average productivity and real GDP at the national level in our baseline relative to a scenario where the Electoral cycle or the post-disaster policies are switched off.

It is evident from panel (a) of Figure 7 that aggregate productivity decreases in our baseline relative to both counterfactual scenarios. The loss is higher when we remove the Electoral cycle and less pronounced when we switch off the post-disaster policies. Removing the post-disaster policies implies no changes in amenity values and transfers and, thus, less population sorting to coastal areas. This results in a lower loss of real GDP relative to our baseline, as highlighted in panel (b).

Relative to our first counterfactual analysis, where the Electoral cycle is switched off, the loss of productivity equals 0.05 percent and real GDP falls by 0.46 percent on average.
Figure 6: Population size after 80 years

Notes: These maps depict the ratio in local population size between current post-disaster policies and counterfactual scenarios after 80 years of simulation and without climate change. The warm color represents more households in the baseline scenario after 80 years relative to the counterfactuals.
Figure 7: Percentage changes in aggregate productivity and real GDP

Notes: These figures depict the changes in aggregate productivity and real GDP from current post-disaster policies compared to counterfactual scenarios without climate change.
after 80 years under the current post-disaster policies. When we switch off the post-disaster policies completely in our second counterfactual analysis, this loss amounts to 0.01 percent and real GDP declines by 0.88 percent on average after 80 years. In other words, we find that the current post-disaster policies in the U.S. lower aggregate productivity and real GDP at the national level.

8.4 Welfare

The population sorting patterns triggered by the removal of the Electoral cycle or the post-disaster policies not only affect productivity and real GDP, but also the endogenous amenity values and congestion forces. In particular, the endogenous amenities do not increase in coastal areas anymore after being hit by a natural disaster in our counterfactual scenarios. This attracts less population to these places compared to the baseline. Unaffected initial donor regions, however, now gain in population size in our counterfactuals. This relaxes local congestion in coastal areas, but lowers amenities in areas receiving an inflow of population due to the increased congestion. Those implied changes in local amenities are essential for the aggregate welfare implications of post-disaster policies. Our measure of aggregate welfare accounts for these local amenities, whereas aggregate productivity and aggregate real GDP do not.

In our baseline, welfare increases by 0.82 percent after 80 years relative to our first counterfactual scenario where we switch off the Electoral cycle. Compared to a scenario without any post-disaster policies, as in our second counterfactual analysis, this gain amounts to 2.10 percent after 80 years. Stated differently, even though the current system of post-disaster policies leads to a loss in aggregate productivity and real GDP, it leads to higher aggregate welfare compared to a scenario without the Electoral cycle. This effect gets even more pronounced relative to our second counterfactual scenario, where we abandon the post-disaster policies. How can we explain this result?

With less (or no) supports from post-disaster policies in counterfactual scenarios, endogenous amenities do not increase in locations hit by a natural disaster. This is because the post-disaster programs are missing to transform public funds into higher-quality amenities valued by the households. We thus find that the population gets less concentrated in the coastal areas affected by natural disasters in our counterfactual scenarios.

Recall that we have quantified the model such that the static dispersion forces are
Figure 8: Percentage changes in Aggregate Welfare

Notes: This figure depicts the changes in aggregate welfare from current post-disaster policies compared to counterfactual scenarios without climate change.

higher than agglomeration forces at the margin. As a result, we also see in our baseline a bigger net increase in amenities (due to a higher concentration of population in coastal areas) than the accompanying productivity losses due to out-migration from the most productive cities. These net donor regions now become more productive in our counterfactuals. Note that some net donor regions are also located at the Atlantic coast in the initial equilibrium (see Figure 5). These places feature high fundamental productivity and amenity levels but are also initially congested in the initial equilibrium. In our counterfactual scenario without post-disaster policies, these places become, however, also much more congested. The latter effect dominates the overall welfare effects in our counterfactual simulations. To summarize, the post-disaster policies are associated with further redevelopment in affected areas on average and increase the level of amenities in the economy. At the same time, these post-disaster policies are financed by over-congested but productive places, which partly mitigates the misallocation of economic activity.
9 Conclusion

Understanding the implications and trade-offs of post-disaster policies is a major contemporary challenge. This paper provides new empirical and theoretical evidence on post-disaster policies' spatial consequences, exploiting the – arguably exogenous – timing of hurricanes relative to Election Day in the US.

We look at counties that were ever hit by a storm between 2001 and 2019 and compare those hit less than a year before ‘Election Day’ (i.e., on-cycle disaster) to those hit more than a year before ‘Election Day’ (i.e., off-cycle disaster). Using an event-study design, we show that on-cycle hurricanes are associated with more generous post-disaster efforts than off-cycle hurricanes. We then document that this effect has sizable implications for the spatial distribution of economic activity. We show that on-cycle hurricanes lead to a significant, immediate, and long-lasting increase in population, indicating that individuals sort into exposed areas after an on-cycle disaster.

We next introduce the relationship between political cycles and post-disaster efforts as a new feature in a dynamic spatial general equilibrium model. In our quantitative simulations, we switch off the impact of political incentives on the allocation of post-disaster grants and abolish post-disaster policies. We simulate the model forward for 80 years, keeping climate conditions unchanged. Under these circumstances, we find that the current system of post-disaster policies featuring electoral cycles leads to population sorting from rich (high-productive) to relatively poor (low-productive) locations, thus lowering average productivity and real GDP at the national level. However, negative congestion externalities and the transformation of public funds into higher-quality amenities matter, such that the abolition of post-disaster policies may even cause a welfare loss. In other words, post-disaster policies may be welfare improving, but they are costly in terms of real GDP and productivity. In addition, the simulations show that current post-disaster policies push economic activity to sort in hazard-prone coastal areas. Therefore, accounting for concurrent disasters, such as sea-level rise, is likely to further tone down these welfare gains.

In times of climate change and increasing disaster risk, policymakers should be aware of these trade-offs – current post-disaster programs might also be costly because of the complex spatial responses they generate.
References


Hornbeck, R. (2012). The enduring impact of the american dust bowl: Short-and long-run


ONLINE APPENDIX

This appendix provides (1) additional empirical results, internal and external validity checks supporting our findings from the main text, and (2) a description of the data, and construction of the variables we use in our quantitative simulations of the importance of the electoral cycle and post-disaster policies for the spatial distribution of economic activity and the aggregate economy.

A Additional Empirical Results

In this part of the online appendix, we provide descriptive statistics, report additional empirical results, and perform robustness tests.

A.1 Hurricanes in the United States

Table A.1 provides a list of the U.S. Hurricanes included in our sample. From 2001 to 2019, 33 hurricanes occurred and all of them happened during a hurricane season, between July to November. The intensity and the wind speed of the tropical cyclones vary across hurricanes. We match the date of hurricanes (Column (1)) to the closest Election Day date (Column (9)) and calculate how many days are left until the next general election when the hurricanes hit. We define a hurricane as an ‘on (off)-cycle’ hurricane if the next election set less (more) than 365 days after the hurricane hits. Table A.2 describes summary statistics for counties ever hit by *Any*, *On-*, and *Off-cycle* hurricanes between 2001 and 2019.

A.2 On-cycle Hurricanes and FEMA Post-Disaster Grants

In this section we investigate whether the timing of hurricanes relative to Election Day serves as a good predictor of FEMA post-disaster grants. The sample considers all counties having ever been hit by a hurricane and received a Presidential Disaster Declaration between 2001 and 2019. Most post-disaster grant programs are run by FEMA (Individual Assistance, Public Assistance, Hazard Mitigation Grant). Because post-disaster grants are earmarked, unique cash flows to economic agents, an event study specification would be less insightful. Instead, we estimate the following specification:
Table A.1: List of U.S. Hurricanes (2001-2019)

<table>
<thead>
<tr>
<th>Date</th>
<th>Subbasin</th>
<th>Name</th>
<th>Max. Wind (kts)</th>
<th>Pressure (mb)</th>
<th>Pressure (mb) of the outermost closed isobar</th>
<th>Radius (miles) of the outermost closed isobar</th>
<th>Radius (miles) of maximum winds</th>
<th>Next Election Day</th>
<th>Days until next Election Day</th>
<th>On-cycle Hurricane</th>
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<td>GM</td>
<td>LILI</td>
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<td>963</td>
<td>1012</td>
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<td>10</td>
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<td>BARRY</td>
<td>65</td>
<td>906</td>
<td>1007</td>
<td>180</td>
<td>40</td>
<td>2020-11-03</td>
<td>479</td>
<td>0</td>
</tr>
<tr>
<td>2019-09-06</td>
<td>NA</td>
<td>DORIAN</td>
<td>90</td>
<td>956</td>
<td>1014</td>
<td>300</td>
<td>25</td>
<td>2020-11-03</td>
<td>424</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: (i) Data displayed in the table corresponds to the date of maximum winds when the hurricane hit the U.S. (ii) Subbasin: ‘GM’ = Gulf of Mexico, ‘NA’ = North Atlantic, ‘CS’ = Caribbean Sea. (iii) The outermost closed isobar determines the maximum extent of the cyclone.
Table A.2: Areas Characteristics by Hurricane Timing

<table>
<thead>
<tr>
<th>Geography</th>
<th>μ</th>
<th>σ</th>
<th>μ</th>
<th>σ</th>
<th>μ</th>
<th>σ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land (km2)</td>
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<tr>
<td>Water (km2)</td>
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<tr>
<td>Latitude (degree)</td>
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<tr>
<td>Longitude (degree)</td>
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<tr>
<td>Total</td>
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<tr>
<td>Male</td>
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<tr>
<td>Female</td>
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<tr>
<td>&lt;15 year-old</td>
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<tr>
<td>[15-64] year-old</td>
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<tr>
<td>&gt;64 year-old</td>
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<tr>
<td>White</td>
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<tr>
<td>Non-White</td>
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<tr>
<td>Households</td>
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<tr>
<td>Household Size</td>
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<tr>
<td>Family Size</td>
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<tr>
<td>Housing Unit</td>
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<tr>
<td>Occupied</td>
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<tr>
<td>Occupied by Owner</td>
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<tr>
<td>Occupied by Renter</td>
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<tr>
<td>Median Value</td>
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<tr>
<td>w/ Mortgage</td>
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<tr>
<td>Median Owner’s costs’</td>
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<tr>
<td>Median Rent</td>
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<tr>
<td>Mobile Homes</td>
<td></td>
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<tr>
<td>Built before 1939</td>
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<tr>
<td>Number of Rooms</td>
<td></td>
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<tr>
<td>No Phone Service</td>
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<tr>
<td>Household Finance</td>
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<tr>
<td>Med. Household Inc.</td>
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<tr>
<td>Average Wage</td>
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<tr>
<td>Ind. in poverty</td>
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<tr>
<td>Personal transfers (M)</td>
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<tr>
<td>Social Sec. trans. (M)</td>
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<td>Medical trans. (M)</td>
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<tr>
<td>Inc. maint. trans. (M)</td>
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<td>Unempl. trans. (M)</td>
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<tr>
<td>Commuters</td>
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<tr>
<td>Education</td>
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<tr>
<td>School Enrolment</td>
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<tr>
<td>College Enrolment</td>
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<tr>
<td>Educ. Att. – &lt;9th grade</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Educ. Att. – High School</td>
<td></td>
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<tr>
<td>Educ. Att. – Bachelor</td>
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<tr>
<td>Miscellaneous</td>
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<td></td>
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<tr>
<td>Foreign Born</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>No English at home</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adults Disabled</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same house 5y ago</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divorced</td>
<td></td>
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</tr>
</tbody>
</table>

Notes: (i) The columns display the year 2000 summary statistics for counties ever hit by Any, On-, and Off-cycle hurricanes between 2001 and 2019 (ii) μ and σ stand for mean and standard deviation, respectively.
Grants_{it} = \alpha_i + \gamma_t + \beta_1 \cdot \text{On-Cycle}_{it} + \beta_2 \cdot \text{On-Cycle}_{it} \times \text{Intensity}_{it} + \epsilon_{it} \tag{24}

where Grants_{it} is the log per capita post-disaster grants a county received conditional on having been hit by a hurricane and having been declared for the related grant program. On-Cycle_{it} indicates whether the hurricane occurred less than 365 days before Election Day, Intensity_{it} stands for the demeaned wind intensity. Here, \( \beta_1 \) captures the impact of an average on-cycle hurricane compared to an average off-cycle hurricane, whereas \( \beta_2 \) captures the additional effect of deviating from the average intensity. Finally, \( \alpha_i \) and \( \gamma_t \) are county and congress-term fixed effects that account for any potential location and time-invariant co-founders.

Table A.3 describes whether counties hit by an on-cycle hurricane are more likely to receive more significant per capita spending from the federal government. Column (1) shows that, conditional on hurricane intensity, being hit by an on-cycle hurricane leads to a 117% increase in the total post-hurricane per capita funds allocated between two Election Days. This effect increases significantly with wind velocities above the mean. This general result is mainly driven by grants targeted to local public infrastructures (as opposed to private relief), through mitigation grants (Column (3)), and grants to local governments (Column (4)). Finally, while average on-cycle hurricanes do not significantly affect per capita grants to private agents, they are sensitive to any above mean wind velocity increase (Column (5)).

The effect is particularly striking when one plots the different coefficients for different wind velocities. In Figure A.1, we can really see that larger per capita grants are channeled to counties hit by on-cycle hurricanes with higher wind speed. Additionally, we show that these results are robust to changing the time frame and treatment definition. Indeed, in Figure A.1 we can see that, within a year, any additional day between a disaster and the next Election day leads to a decrease in the per capita grants received – but only for strong hurricanes. A potential mechanism for this heterogeneity could be that, precisely because of the electoral campaign, a weak storm receives less attention than it would off-cycle – i.e., news crowds out other news.

The results are consistent with what previous literature has found that state governments’ bailout activities are more responsive where the electoral accountability is greater.
Table A.3: On-cycle Hurricanes and Post-Disaster Grants

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All grants</td>
<td>Relief grants</td>
<td>Mitigation grants</td>
<td>To Public</td>
<td>To Private</td>
</tr>
<tr>
<td>On-Cycle</td>
<td>1.171***</td>
<td>1.126***</td>
<td>1.367***</td>
<td>1.407***</td>
<td>-0.285</td>
</tr>
<tr>
<td></td>
<td>(0.288)</td>
<td>(0.284)</td>
<td>(0.297)</td>
<td>(0.269)</td>
<td>(0.336)</td>
</tr>
<tr>
<td>On-Cycle × Intensity</td>
<td>0.143***</td>
<td>0.140***</td>
<td>0.139***</td>
<td>0.130***</td>
<td>0.192***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.025)</td>
<td>(0.021)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Observations</td>
<td>498</td>
<td>498</td>
<td>498</td>
<td>498</td>
<td>371</td>
</tr>
<tr>
<td>County FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Congress FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.65</td>
<td>0.64</td>
<td>0.64</td>
<td>0.66</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is the log per capita post-disaster grants a county received conditional on having been hit by a hurricane and having been declared for the related grant program. Standard errors are clustered at the county level and are reported in parentheses. The observation is at the yearly county level between 2001 and 2019. The sample considers all counties having been hit by a hurricane and received a Presidential Disaster Declaration. The post-disaster grant programs are run by FEMA (Individual Assistance, Public Assistance, Hazard Mitigation Grant) and the Small Business Administration.

(Besley and Burgess, 2002; Strömberg, 2004). Previous studies also show that governments appear to be more generous with disaster relief during election years, which can lead to suboptimal policy outcomes (Cole et al., 2012). In addition, the literature has argued that relief grants are generally favored over mitigation grants because voters have a clear pre-disaster counterfactual to judge their representative’s action (Healy and Malhotra, 2009). Here, our results confirm the hypothesis that post-disaster efforts are indeed driven by political incentives, but relief (Column (2)) and mitigation grants (Column (3)) are evenly favored during on-cycle events.
Figure A.1: Impact of Hurricane Timing on Post-Disaster Grant

Notes: (i) The top panel displays the impact of on-cycle disasters on post-disaster grants ($\beta_1$ in Equation 24) (ii) The top panel displays the impact of an extra day between a disaster and the next Election Day on post-disaster grants (iii) Wind intensities: tropical depression winds ($\leq 18$ m/s), tropical storms winds (18-32 m/s), hurricanes winds ($\geq 32$ m/s – measured from the CLIMADA wind field model), max. hurricanes winds ($\geq 32$ m/s – measured from the radius of maximum winds).
A.3 Population Results Demographics

The main population sorting pattern is characterized by a permanently increasing sorting of white individuals compared to non-white, both in the on- and off-cycle cases. This could indicate a sorting on race, linked to a local gentrification phenomenon. This idea is also supported by the results of section A.4.

Furthermore, Figure A.3 indicates that the on-cycle population sorting is characterized by an increasing labor supply as a result of the post-disaster efforts.

A.4 GDP and Employment Rates by Industry

In this section, we explore how on-cycle and off-cycle hurricanes affect employment shares and GDP by industry. Not surprisingly, the results presented in this section appear to be driven mainly by infrastructure development – i.e., construction, professional services (engineers, architects, etc.), finance, insurance, and real-estate sectors. We also find that food, coffees, and general accommodation services appear to benefit from on-cycle disasters, which, taken together with the other sectoral changes and the local demographic changes, points towards a gentrification phenomenon of the counties impacted by on-cycle disasters. Last but not least, on-cycle disasters also seem to positively influence the output growths of the government, health, and education sectors. This is in line with Table A.3 showing that on-cycle disasters have a more significant impact on post-disaster grants to public (as opposed to private) entities.

A.5 Housing Values

In this section, we use our main empirical strategy to test if median housing values and housing values volatility (measured by a standard deviation in the monthly mean values) react predominantly to on-cycle or off-cycle hurricanes. We use the Zillow Home Value Index (ZHVI) which is a smoothed, seasonally adjusted measure of the typical home value and market changes across a given region and housing type. It reflects the typical value for homes in the 35th to 65th percentile range. In this sense, the ZHVI represents the “typical” home value per location (e.g., county) now and over time. Figure A.4 supports the notion that on-cycle disasters trigger population inflows.
A.6 Alternative Political Dimensions

In this section, we run further checks on how electoral incentives may affect population sorting. Indeed, it may be that the population sorting result is driven not by the electoral cycle, but by a concurrent apolitical mechanism. Using alternative political dimensions (namely, political alignment with the executive power, local partisanship, and swing state status) shows support to our main hypothesis: post-disaster political efforts cause population sorting.
Figure A.3: On-cycle vs. Off-cycle Hurricane Treatment Effect on Labor Force Status Ratio

Notes: This figure plots event study estimates and corresponding 95 percent confidence bands of different specifications of equation (1). The dependent variable is the difference between log labor force population and population out of labor force. Event variables are dummies equal to 1 for a hurricane. The estimation sample comprises all treated and not-yet-treated counties. The regression model includes county, and year fixed effects. Standard errors are clustered at the county level.
Figure A.4: On-cycle vs. Off-cycle Hurricane Treatment Effect for Median and Price Volatility of monthly Housing Values

Figure A.5: Treatment Effect by Political Alignment, Partisanship, and Electoral Competition

Notes: This figure plots event study estimates and corresponding 95 percent confidence bands of different specifications of equation (1). The dependent variable is the log population. Event variables are dummies equal to 1 for a hurricane. The estimation sample comprises all treated and not-yet-treated counties. The regression model includes county and year fixed effects. Standard errors are clustered at the county level.
A.7 IRS Tax returns County-to-County Flows

To better understand how population sorting operates after an on-cycle hurricane, we split the population stock into flows of stayers, movers in (inflow), and movers out (outflow) using the IRS county-to-county migration data. When one regresses each flow separately against our main treatment, we observe that the increase in population after on-cycle hurricanes seems to follow an increasing number of people deciding to stay. While giving some insights, the IRS data limitations, however, prevent from providing a straight interpretation of these results.

![Figure A.6: On-cycle vs. Off-cycle Hurricane Treatment Effect on Population Flows](image)

**Figure A.6: On-cycle vs. Off-cycle Hurricane Treatment Effect on Population Flows**

*Notes:* This figure plots event study estimates and corresponding 95 percent confidence bands of different specifications of equation (1). The dependent variable is the total population, and the number of stayers, inflows, and outflows. Event variables are dummies equal to 1 for a hurricane. The estimation sample comprises all treated and not-yet-treated counties. The regression model includes county and year fixed effects. Standard errors are clustered at the county level.

A.8 Robustness Checks

In this section we test the robustness of our main results to alternative estimators. Figure A.7 documents that the main population response remains qualitatively similar when applying Borusyak and Jaravel (2017)’s, Sun and Abraham (2020)’s, or the traditional OLS estimators. Similarly, Figure A.8 shows that the result also remains essentially unchanged when using counties never hit by a hurricane in our sample period as a comparison group and/or controlling for wind velocity upon landfall.
Figure A.7: On-cycle vs. Off-cycle Hurricane Treatment Effect on Log Population using Alternative Estimators

Figure A.8: On-cycle vs. Off-cycle Hurricane Treatment Effect on Log Population using Never Treated for Comparison (first line) or Controlling for Wind Velocity (first column)
A.9 External Validity

In this section, we provide supportive evidence about the generality of our main result that also extends to other time frames, locations, treatment definition, and types of disasters. First, we check if our main result is not the product of recent extreme weather events and extend our analysis period to 1969. Figure A.9 documents that population increases dramatically in counties hit by on-cycle hurricanes, even before the 2000s. Exploiting the full wind field distribution, Figures A.11 and A.12 document that only large wind speeds are likely to drive the sorting response. Yet, we check that our main result does not come from a specific type of disaster and use wildfires and floods as treatment. To do so, we collect information on the 500 largest wildfires between 1988 (i.e., the year of the Stafford Act) and 2019 from the Interagency Fire Perimeter History dataset. Figure A.13 documents that population also significantly increases in counties hit by on-cycle wildfires as opposed to off-cycle wildfires. We also collect information on extreme flood events not generated by storms or hurricanes over the same period from the Dartmouth Flood Observatory (DFO) (Kocornik-Mina et al., 2020). Again, Figure A.14 documents that the population significantly increases in counties hit by on-cycle floods as opposed to off-cycle floods.
Figure A.9: On-cycle vs. Off-cycle Hurricane Treatment Effect on Log Population (1969 – 2019)

Figure A.10: On-cycle vs. Off-cycle Hurricane Treatment Effect on Log Population before and after the Stafford Act
Figure A.11: On-cycle vs. Off-cycle Minor Hurricane Treatment Effect on Log Population

Figure A.12: On-cycle vs. Off-cycle Major Hurricane Treatment Effect on Log Population

Figure A.14: On-cycle vs. Off-cycle Flood Treatment Effect on Log Population (1988 – 2019)
A.10 Non-Disaster Transfers

In this section, we check if natural disasters occurring close to Election Day also affect other non-disaster transfer types as in Deryugina (2017). Overall, counties hit by on-cycle disasters receive decreased per capita non-disaster transfers from governments compared to counties not yet hit by similar disasters. This result is mainly driven by increasing post-disaster population. Only unemployment benefits per capita increase after an on-cycle hurricane. Non-disaster transfer growth from businesses and non-governmental organizations (e.g., charities) are not impacted by on-cycle hurricanes.
B Quantitative Analysis of the Model

This Appendix describes the data sources and the variable definitions that we use in Section 7, details some further issues related to the definitions of our variables, and presents the details of our estimates in the quantification of the model.

B.1 Data sources

Geographical land area. \( H(\cdot) \) from the 2010 Census Gazetteer Files.

Wages. \( w_0(\cdot) \) as GDP per capita from the Bureau of Economic Analysis (BEA) website, under Regional Data, Economic Profiles for all U.S. counties. Wages are normalized to have a mean of one.

Total population. \( L_0(\cdot) \) from the U.S. Census and Surveillance Epidemiology and End Results (SEER) population database for all U.S. counties. We use data on the population distribution for each year between 2001 and 2019 to obtain \( L_t(\cdot) \). For each year, we transform population into population per unit of land.

Human Development Index (HDI) on subjective well-being. We calculate a proxy similar to the Human Development Index (HDI) on the county level as our measure for \( u_t(\cdot) \). Following Desmet et al. (2018), we then transform it into a cardinal measure of the level of well-being and normalize it to have a mean of one.

Tax and transfer rates. \( t_0(\cdot) \) and \( \theta_i^b(\cdot) \) for \( i = C, G \). To calculate the tax and transfer rates, we use the Government Finance Database (Pierson et al., 2015) which provides information on government revenues from the U.S. Census Bureau’s Census of Governments and Annual Survey of State and Local Government Finances collected by the federal, state, and local governments.

At each of these different jurisdictional layers, taxes on various sources are imposed. The most prominent tax sources are income, payroll, sales, property, capital gains, dividends, imports, estates, and gifts. In our baseline year 2001, total taxes collected by federal, state, and local governments together amounted to 25% of GDP. Over two-thirds of taxes in the U.S. are collected by the federal government, where social insurance and retirement, corporate, and individual income taxes account for almost all the federal tax
revenues. The remaining tax revenues are collected by the states and local governments. States’ tax revenues come mostly from income and sales taxes. Each county collects and keeps a certain amount of its own tax revenue, where property taxes account for the majority of local tax collections.

To calculate a proxy for all collected taxes per county, we assign exclusive Federal and State tax revenues to the local level according to their population shares. This allocation rule captures the idea that counties with higher population shares are characterized by higher economic activity in general, which implies higher revenues also from other taxes. Finally, dividing tax revenues by local GDP as reported by the Bureau of Economic Analysis yields average tax rates.

Next, we compute local public budgets after redistribution. Here, we directly draw on data on public expenditures at the county level. These local expenditures include transfers from other jurisdictions and upper governmental layers, like the Federal government and the States.

Combining collected taxes from step one and the available public budgets from step two finally delivers net transfers per county that we can relate to local GDP to obtain transfer rates.

**Trade costs.** $\zeta(\cdot, \cdot)$ from detailed geographic information on the rail, road, and water networks. We calculate instantaneous trade costs between every county in the US using the “fast marching method” algorithm cost based on the function parameters as assigned in (Allen and Arkolakis, 2014).

**Synthetic hurricane paths.** To calculate synthetic hurricane paths for the years 2001 - 2081 in the US, we use the STORM dataset (Bloemendaal et al., 2020). The data uses historical data from the IBTrACS repository to predict more than 10,000 hurricane synthetic tracks and corresponds to current climate conditions. Figures B.1 and B.2 shows examples of the distribution of on- and off-cycle hurricanes in this dataset.
Figure B.1: On-cycle vs. Off-cycle Synthetic Hurricane Tracks over 100, 250, 500, and 1000 years.

Figure B.2: On-cycle vs. Off-cycle Synthetic Hurricane Radius of Maximum Winds over 80 years.
B.2 Parameter estimates

In this section, we provide further details about our estimates of the impact functions. Figure B.3 shows that amenities and local transfer rates increase after a natural disaster on average.

![Figure B.3: On-cycle vs. Off-cycle Hurricane Treatment Effect on Amenities, Productivities, and Transfer Rates](image)

Notes: This figure plots event study estimates and corresponding 95 percent confidence bands of different specifications of equation (1). The dependent variables are the logarithm of fundamental amenities, the logarithm of the ratio of fundamental productivities to innovations, and the logarithm of transfer rates. The transfer rate has been rescaled such that the minimum is positive, according to $(\theta(\cdot) - \min \theta(\cdot))/(\max \theta(\cdot) - \min \theta(\cdot))$. Event variables are dummies equal to 1 for a hurricane. The estimation sample comprises all treated and not-yet-treated counties. The regression model includes county and year fixed effects. Standard errors are clustered at the county level.
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Contact of the authors:

Marcel Henkel
University of Bern
Schanzeneckstrasse 1
P.O.Box
CH-3001 Bern
Telephone: +41 31 684 47 92
Email: marcel.henkel@unibe.ch

Eunjee Kwon
University of Cincinnati
LCB-Finance
LINDHALL 2341
2906 Woodside Drive
Cincinnati OH 45221-0195
Telephone: (323)571-7821
Email: kwonee@ucmail.uc.edu