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Three Essays on Understanding Social and Economic Responses to Crisis and Disaster Events

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THREE ESSAYS ON UNDERSTANDING SOCIAL AND ECONOMIC RESPONSES TO CRISIS AND DISASTER EVENTS

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by

Shahnawaz Mohammad Rafi

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To: Dean John F. Stack, Jr.
Steven J. Green School of International and Public Affairs

This dissertation, written by Shahnawaz Mohammad Rafi, and entitled Three Essays on Understanding Social and Economic Responses to Crisis and Disaster Events, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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The dissertation of Shahnawaz Mohammad Rafi is approved.

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Florida International University, 2022

DEDICATION

This dissertation is dedicated to my mother, my charming wife, Tania, for her unconditional support and inspiration, my kids, Raeeda and Nabeeha, for their warmth, and the rest of my family for their unending love, support, and encouragement.

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ABSTRACT OF THE DISSERTATION

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Professor Pallab Mozumder, Major Professor

The dissertation is composed of three chapters focusing on analyzing social and economic responses to crisis and disaster events. In the first chapter, we have investigated whether media affects the U.S. official foreign aid channel or crisis-needed aid. We have examined natural disaster citations in four mainstream U.S. newspapers to analyze whether they influence the Official Development Assistance (ODA) or the short-term crisis-based need of a recipient following a natural disaster. With that objective, we created three new media variables to measure the strength of media effect on US ODA, humanitarian, and food aid. The empirical analyses indicate that media citation only affects crisis-needed food and humanitarian assistance.

Every year hurricanes of different intensities make landfall in the mainland U.S. The devastation and havoc of those hurricanes often have long-lasting effects on people's livelihood, infrastructure, and homes. The deadliest hurricane ever recorded in Puerto Rico, Hurricane Maria, made landfall in 2017. Hundreds of thousands of homes were damaged, and millions of people lost power for months. In the second chapter, we investigated how the devastation of Hurricane Maria affected the housing prices in Puerto Rico. We gathered

home sales data in Puerto Rico from Zillow a leading multiple listing service (MLS) platform for real estate in the U.S. We combined the hedonic price model with Regression Discontinuity Design (RDD) to quantify Hurricane Maria's causal (treatment) effect on housing prices in Puerto Rico.

In 2017, another hurricane (Hurricane Harvey) wreaked havoc on Texas. Floodwaters inundated homes in Texas and disrupted utility services. Hurricane Harvey resulted in significant economic and social consequences by disrupting public utility services such as power outages, phone service interruptions, and transportation service disruptions. The interruption in one sector impacted the operation in other interdependent sectors. In the third chapter, we used household survey data to analyze the performance of critical infrastructure systems and the impacts of utility disruptions in Houston, Texas. Then we incorporated the household survey responses into the Dynamic Inoperability Input-Output Model (DIIM) to estimate inoperability and economic losses in multiple linked sectors. This chapter also assessed the top ten inoperable (stalled) sectors.

Overall, the goal of this dissertation is to understand and evaluate the impact of natural disasters at the Macro (U.S.), Meso (Puerto Rico), and Micro (Houston) levels.

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Chapter 1

Role of Media Effect on U.S. Aid: Assessing Development Aid, Humanitarian Assistance, or Food Aid.

1.1 Introduction:

Assessment of allocations has been an indispensable avenue of foreign aid research since the early 21st century. The literature has been dominated by the determinant of aid allocation (Alesina & Dollar, 2000), the effectiveness of utilization (Ali & Isse, 2006), reducing corruption and enhancing governance (Alesina & Weder, 2002), growth increase by aid (Burnside & Dollar, 2004; Easterly, 2003). Several scholars (Drury et al., 2005; Strömberg, 2007; Van Belle, 1999) have also identified that natural disasters and media are significant contributors to aid determination. The global coverage of natural disasters in the donor media generates a moral resonance in electronic and print media and facilitates aid disbursement in affected places.

The ever-developing literature on media and aid showed that foreign aid allocation in the past was responsive to media exposure, and it was substantial when combined with natural disasters. Many of these researchers (Eisensee & Strömberg, 2007; J. S. Kim, 2005; Van Belle & Hook, 2000) investigated the impact of media on individual aid types. For example, Official Development Assistance (ODA) commitment, disbursement, or emergency aid (food or humanitarian) disbursement. Their inferences on the media-aid-disaster nexus helped to conduct future research. But the portrayal of major incidents in a recipient country in the donor media is a usual procedure irrespective of any natural disaster. We think the past analysis of disaster and media-led foreign aid allocation only showed a partial picture of their connection. We do not know whether the aid-media nexus is an emergency event (natural disasters) or, in general, ODA specific. It is also questionable whether the media effect was significant on the ODA commitment or disbursement. We attempted to settle that score.

This paper aims to determine whether a media-driven foreign aid allocation decision is an emergency (natural disaster) or a development activity-specific event. Therefore, we analyzed the media effects on ODA and emergency assistance from a broad perspective. We also like to determine whether this media effect is dominant in commitments or disbursements. We created a new set of media variables which is unique in the literature. We constructed our media variables based on newspaper stories, termed them as citations, and divided them into general news, disasters, and ODA-related news. Finally, we want to understand if disaggregated media variables would improve the prevalence of media on aid.

Our study is limited to foreign assistance from the U.S., a key donor of aid to the Organization for Economic Cooperation and Development (OECD). The OECD Development Assistance Committee (DAC) repository is the source of the ODA data. We collected the ODA commitments and disbursements data between 1966 to 2014. Our dataset also included humanitarian aid from 1995 to 2014 and food aid between 1975 to 2014.

We used a Panel Fixed Effects (F.E.) regression for data analysis. The inclusion of citation variables in the regression analysis was our primary identification strategy. We estimated log level and per capita aid regression, which helped us explain the selection of our identification strategy. Furthermore, the identification technique allowed us to infer whether media coverage of a country was a significant factor in U.S. aid allocation decisions.

The findings of our paper have significant implications for media-foreign aid relationship research[1]. There was no significant impact from any news citations on the overall ODA disbursement; however, the disaster and ODA news citations affected the ODA commitment. Again, not a single per capita citation significantly impacted the overall ODA commitment and disbursement. Hence, this insignificance outcome of media citations deviates from the previous significant research findings (Eisensee & Strömberg, 2007; Olsen et al., 2003; Potter & Van Belle, 2009; Van Belle & Hook, 2000). We conclude that the media effect is more dominant in ODA commitment than disbursement. The other determinants of foreign aid, such as trade, PGDP, U.S. alliance, and democracy status, are strongly aligned with previous research findings (Alesina & Dollar, 2000; Ali & Isse, 2006; Zimmerman, 2007).

We think the effects of media citations are particularly salient for emergency events. To support our idea, we compared emergency aid disbursements with ODA commitments (disbursements). We found that each newspaper citation significantly induced the flow of U.S. food aid per capita. Similarly, foreign news content in U.S. newspapers notably impacted U.S. humanitarian aid disbursement. We did not discover any meaningful influence of newspaper citations on ODA commitment or disbursement in the same time frame of food and humanitarian aid. The only exception was that the ODA news citation affected the ODA disbursement.

[1] The analysis is done for the U.S. ODA commitments and disbursements for an extended period from 1966 to 2014. We considered a short data span from 1995-2014 to compare humanitarian aid disbursements, ODA commitments, and disbursements. A similar approach applied for the comparison between food aid disbursement, ODA commitments, and disbursements, from 1975-2014.

This paper is divided into six sections. Section 1.2 delves into the variables that influence foreign aid funding and the role of newspapers. We provide data and methodology explanations in section 1.3. The results are presented in Section 1.4, and policy implications and discussion in section 1.5. The study concluded in Section 1.6, including a bibliography and an appendix.

1.2 Literature Review:

It is important to investigate why the U.S. print media publish international stories to understand how media impacts aid delivery. The appendix Table 1A1 provides a synthesis of the literature on this. In the late 90s, Chang et al. (1987) found four significant factors that determined whether a global event is publishable or not. These are normative aberrancy of an event, whether the event is relevant to the U.S., events that have the potential for social change in the U.S., and geographic distance[2] between the U.S. and the aid recipient. They pointed out that Western donors' international news agency ownership also creates an imbalance of publishable news content on developing country contexts.

The foreign aid and media literature is emerging rapidly; Simon (1997) compared the U.S. earthquake relief efforts across three sources, private contributions from citizens, the U.S. government, and international agencies. His finding showed that the media coverage impact on U.S. government disaster relief was much smaller. The outcomes also indicated that network news substantially affected U.S. private contributions and had little effect on international relief efforts. Even though his sample was much smaller and

[2] Wu (1998) validated geographic distance between the U.S. and neighboring nations (North Canada and South Mexico) is a primary determinant of media attention. It has a powerful effect

confined to the earthquake[3], his finding shed light on avenues where media may not be predominant as expected.

The media and foreign aid allocation dynamics can differ by the types of media (newspaper vs. television news). Van Belle (1999) tested their connection using data from the Vanderbilt News Index and the New York Times Index and they found[4] that the development aid was politically motivated, while emergency aid was not. Again, a competition between U.S. domestic news[5] coverage and contemporary foreign disaster news sometimes makes it difficult to judge their relationship. Hence, the US considers domestic factors like the budget deficit, disasters, and the salience[6] of international disasters when receiving a plea for aid from a foreign nation (Drury et al., 2005). The media effect was significant. According to them, if newspapers published ten or more stories, each increased the probability of annual aid allocation by three percent.

To further check the effect of media on ODA, Van Belle and Hook (2000) studied variations in the US ODA commitments in response to U.S. network television news coverage of foreign countries. The news coverage variable was significant in their analysis and boosted US ODA commitment between 1977-1992. Drury et al. (2005) explored the effects of newspaper citations on the US ODA allocation using foreign disaster coverage from U.S. network television news. Their results showed that a single citation in the New

[3] The data was gathered from all 22 earthquakes between 1972 and 1990 and resulted in 10 or more deaths.

[4] Belle (1999) uses the Vanderbilt New Index televison news coverage data.

[5] The New York Times (NYT) citation on natural disasters used as a source of media coverage.

[6] The salience of the international event was measured in terms of their reflection in the NYT.

York Times (NYT) accounted for an average disbursement of over $1 million ODA per year to disaster-affected countries.

In general, the international news coverage of disasters in donor countries has decreased over the years, making the link between aid and the media less effective. There are two prominent reasons behind this downfall. First is integrating traditional news sources into the digitalized platforms and widespread social media use. Second, the closure of many foreign news bureaus[7] and a significant drop[8] (13%) of foreign news in the major US television networks from the 70s to 90s (Halton, 2001). A typical foreign story that does not involve financial misery, bombs, or natural disasters is unlikely to make it into the minds of Americans through the news (Arnett, 1998; Halton, 2001). This impression encompassed that foreign news coverage in the U.S. media outlet is very selective.

Media alone cannot influence the aid decision process. This thinking led Olsen et al. (2003) to conclude that emergency assistance volume factors work in conjunction or individually, and only occasionally[9] media play decisive roles in the process. According to the authors, dramatic, credible imagery of each crisis help U.S. media to decide the intensity of any disaster and subsequent media coverage. Massive media coverage of a calamity increased the possibility of emergency fund allocation. Still, it did not produce as

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[7] Halton (2001) claims the factors that contributed to the decline are growing media ownership concentration based on profit, changing the news' content and quantity. He also thinks the decrease depends on the expense of operating an overseas office, staff correspondent's travel costs.

[8] This data was collected from a survey conducted by the Joan Shorenstein Center at Harvard University that found the time on network television dedicated to international news.

[9] They explored the notion of periodic disaster by simultaneously using several case studies.

much disbursement as expected because the media attention of a donor changes frequently[10]. As a result, the media effect of foreign disaster coverage on aid may not be as strong as the authors argued. They also claimed that the geopolitical interest of a donor was another dominant factor in the aid dynamic.

Donor nation's domestic security concern is another critical factor in aid allocation. This consideration led Potter & Van Belle (2009) to assume that the media's role in development aid is weaker than the other determinants. They also argued that the media's authority was relevant for disaster aid because it is event-driven and involves short-term policy decisions. The U.S. has a fixed set of geographic commitments for assistance, and media coverage may further strengthen those commitments, specifically during an emergency. Hence, foreign disaster news coverage in the donor country's newspaper directly affects emergency assistance.

The salience of media coverage variables was the focal point of aid-media literature. Newspaper and television coverage influences U.S. foreign aid, but newspapers consistently perform better than television news coverage (Van Belle, 2003). Because newspaper coverage is comprehensive, whereas a television program has time restriction (Van Belle & Potter, 2011a). Hence, we select print media as the platform for our research because the time constraints[11] of television news may alter our findings.

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[10] Olsen et al. (2003) referred to this phenomenon as a news-attention cycle.

[11] The average length of evening news on US television is 30 minutes (*News Coverage Index Methodology | Pew Research Center, n.d.*)

The donor interests (trade, security) donor or a recipient's need (development or humanitarian) determine foreign aid allocation. Apart from these factors, epidemic, war, and natural disaster significantly influences aid disbursements. When these events happen unexpectedly in a recipient nation, they generate public sentiments[12] in a donor country and receive widespread media attention. Foreign aid lobbyists and activists then create awareness about the urgent nature of these events and place them on the agenda of the policymakers. So, a mention of these disasters was circulated five times in primary U.S. media sources over five years; a disaster-stricken country then received an additional 1% per capita U.S. aid (J. S. Kim, 2005).

The media's effect on donors' aid policy is then judged based on the perception of foreign policy stakeholder's and the public's sympathy for those events (Martin, 2005; Van Belle & Hook, 2000). Because non-state actors work at the core of media-aid dynamics, and in the process, non-exposed countries receive less support in the donor country's media. Hence, Van Belle & Hook (2000) argued against considering different/multiple motives behind the U.S. government's aid allocations and media coverage[13].

News media is a proxy for understanding the foreign aid need of recipients and framing them in the eye of the public in a donor country. Therefore, the media serve as a readily available measure of domestic political significance; hence more coverage of a less developed nation led to increased aid assistance pledges (Rioux & Van Belle, 2005).

[12] J. Kim (2005) thinks researchers see the media as a "proxy" for public opinion in the perspective of policymakers. Foreign policy professionals in donor nations function as public custodians, responding to public opinion when formulating policy decisions.

[13] Van Belle & Hook (2000) showed that the coefficient of TV Stories in every network television news would increase US ODA commitments approximately by $230,000.

According to their estimation, French media covered more stories about their former colonies or places where French is the official language. As a result, those nations received a bulk of French development aid.

Media-led foreign aid policy depends on how the U.S. bureaucracy contemplates the media effect. Van Belle (2003) believed that the New York Times and television's nightly news broadcasts were essential predictors of media in measuring bureaucracy's response to ODA obligations and disaster relief. As a result, media coverage is a vital component of U.S. foreign policy (Van Belle & Potter, 2011a). But bureaucracy's role in media-centered ODA policy is not straightforward. Public awareness can press the bureaucracy channel to include any urgent need via media pressure. Hence, Van Belle & Hook (2000) argued that the bureaucracy would respond to public sentiment until foreign policy's institutional and financial discretion had discoursed.

The post-Cold War foreign policy played a significant role behind the scenes as the driver of bureaucracy-led foreign aid allocation. Jolly (2014) restated that media-affected bureaucratic responsiveness was a strong driving force in U.S. aid disbursement. Many of these aid disbursements relied on the bureaucratic response and donor country structural shifts over the years. Policy processes may change because of unplanned events, institutional policy shifts, or unduly complex bureaucratic transformation (Joly, 2014).

News media influences the ODA commitment decision of a donor country's foreign policy planners. As a result, the news media provides essential information regarding international political events and activities to voters, interest groups, and those engaged in political decision-making (Potter & Van Belle, 2004). They also argued that news media salience was a crucial indicator of a domestic political issue and foreign aid disbursements.

Therefore, higher news coverage of a developing country would increase the amount of development aid from a donor. Our paper acknowledges the substantial implications of these public reflections and media conjoint on ODA commitments.

Developing countries receive more attention in donor countries' print media than network television news (Potter & Van Belle, 2004). According to the authors, there is a time constraint between domestic and foreign news reports on the television news segment. Newspapers distribute a fixed amount of space for foreign information. Hence, regardless of any dominant domestic story in the donor media, natural disaster-related foreign news or relevant events can receive more newspaper coverage. This advantage of newspapers over television led us to focus our work solely on newspapers. In our data collection process, we emphasized headline news and news coverage on the front page, which we assume should increase the chance of U.S. aid allocation. Hence, considering cases that receive no media attention, the likelihood of aid increased by 61% when the disaster news published on the front page right after a natural disaster (Joly, 2016)

We think the variation in the aid flow is due to the irregular media coverage of foreign news in donor media. The donors' media may not highlight a significant foreign event. This lack of foreign information critically impacts the policymaker's development agenda. Sometimes donors lack direct media correspondence in a foreign country. Hence, they subcontracted news from foreign news sources, resulting in less coverage, less context, and fewer donors' dimension to stories of the developing world news (Martin, 2005)[14].

The media agenda rotate promptly. As a result, media salience indicators also alternate so rapidly that they may weaken their net impact on aid. Hence, the decision-makers also need to accommodate to adjust their schedule expeditiously[15]. Martin (2005) termed this trend as 'parachuted' to the next 'scoop' because the readers never see the rebuilding that occurs, and it leaves the vital job that development aid could have otherwise achieved out of the audience's view. We methodologically ruled out this persistent news pattern because our paper focuses on how newspapers' coverage of a foreign natural catastrophe motivates U.S. policymakers in a static setting.

The accuracy and transparency of news reports, mainly reporting natural disasters, are essential in assessing the media's impact on foreign aid allocation. These reports focus on the intensity of the disaster and its influence on the need for humanitarian assistance. The close ties between aid and media led China to implement a "State Master Plan for Rapid Response to Public Emergencies" policy in 2006. This policy assured that the Chinese media would deliver consistent and appropriate information to the public(Wei et al., 2009). But the implication of this policy required a constant flow of authentic news, which is not the case in most cases. Thus, Mason (2011) doubted the media's role in aid-giving; he was cautious, mainly due to the donors' overshadowed disaster information collection, which will not present the affected country's real distress scenario.

[14] For example, Martin (2005) stated that Canadian media outlets tend to lack international offices and field reporters, leading to reliance on foreign news sources, especially wire services (such as Associate Press or Reuters).

[15] Similarly, Eisensee & Strömberg (2007) found that the life cycle of the disaster news is about 20 days.

The disbursement of disaster aid depends on the media's relative weight of disaster coverage. Eisensee and Strömberg (2007) argued that domestic news and contemporary newsworthy materials coverage in the U.S. media crowd out foreign disaster coverage. They measure median minutes allocation to the top three topics in U.S. television's evening news and termed it news pressure. The authors tracked the duration of this news pressure up to 40 days in the post-disaster scenario. They concluded that higher news pressure reduces the probability of U.S. emergency assistance to affected places. Our approach is novel from their analytical approach. We tested newsworthiness by the number of times newspapers published a story of disasters in a year. Our measurement assumed that more newspaper citations of disasters would increase aid allocation in the affected countries.

The severity of disasters should be the primary criteria for considering their newsworthiness. But, Joye (2010) thinks the geographical location of a disaster strongly biases Western newspapers' coverage. He compared exposures across continents. His analysis found that European disasters occupied 3800 cm^2 space in Belgian newspapers, whereas Asia, Latin America, and African disasters got one-third (1100 cm^2) of the European coverage.

The nature of media-led development aid is different from media-driven humanitarian assistance. The former requires consistent and significant exposure on mainstream media platforms, whereas natural disasters predominate the latter. Van Belle (2009) tested the media's saliency on five donors, including the U.S. He stated that media coverage was always statistically significant, regardless of the mixture of independent factors employed and style of analysis or medium used to indicate salience.

When a donor newspaper publishes and conveys the importance of a foreign event to U.S. policymakers, it should attract more ODA for these places. This notion is commonly known as media visibility in aid-media literature. Jones et al. (2013) think the justification of this notion of visibility or worthiness depends on assessing the magnitude of U.S. ties[16] with a recipient.

U.S. newspapers procured foreign news content from international agencies like Reuters Associated Press (A.P.) and Agence France-Presse (AFP). The worldwide media coverage of these organizations had a positive correlation and was a crucial influencer of assistance distribution (Lim et al., 2008). Hence, the media visibility of those news stories in these news agencies could turn decision-makers myopic because of intense media pressure about a particular event, and they could misjudge it (Joly, 2014).

Cawley (2015) thinks donor media's lower visibility of foreign events and prioritizing domestic incidents generate pressure on elected political officials and divert foreign aid. Here, the press acts as an agent for public reflection to create an institutional resistance to aid allocation[17].

Countries with low incomes and a lack of democracy are physically and culturally isolated from major donors. They may not be under the consideration of foreign aid when stricken by natural disasters. Hence, Strömberg (2007) thinks that countries with historical ties, vital for a donor's foreign policy or economic objectives, and are similar

[16] These factors are geographical proximity, trade flows, and number of US troops presence in the recipient nations. Addition to those their economic strength (GDP) and total population also considered.

[17] Cawley's (2015) research's main contribution is identifying variables that are important for journalists to decide whether international news is worth publications in the U.S. or not considering their own domestic circumstances.

geographically or culturally receive more aid. His analysis revealed that around 29 percent of the foreign disasters in U.S. newspapers received 16 percent more than those not covered.

The effect of the media-disaster duo on aid can differ by the timing of research conducted. Immediate media exposure in the donor media and the relief effort significantly influenced donors' post-disaster aid initiatives (Becerra et al., 2014). We do not confine our study to a post-disaster specific point of time; instead, our primary aim is to validate whether media influence aid. Therefore, we focused our analysis on ODA commitments, disbursements, food, and humanitarian assistance.

There is limited evidence about the short and long-term effects of media-led foreign aid allocation. We assumed that the magnitude of impact varies by the type and timing of the disasters and the U.S. newspaper's disaster news placement. Joly (2016) proposed that the timing of media attention influences foreign aid decisions, with short-term[18] consideration determining which nations get help and long-term involvement resulting in the approval of the aid amount. Our analysis projects the long-term viewpoint of aid allocation.

Aid-media paradigm investigation from an individual donor-recipient point of view is standard in the literature. In contrast, the worldwide media coverage of a natural calamity can scrutinize aid allocations' global structure. Hence, the network analysis assessment of media salience on aid highlights the pattern of international assistance among nation-states and international governmental organizations (Lim et al., 2008). They reasoned that better global news coverage of disasters generates more aid for the affected locations. This

[18] The short-term impact of agenda setting mechanism is often known as the CNN effect.

network analysis research is more relevant in computer science, but the result implied that media profoundly impacted aid.

Finally, the media-aid literature found the relationship between media and U.S. national interest criteria of aid allocation was relatively weaker. The U.S. strategic interest in some geographic regions leads to deploying more U.S. troops in those regions, such as the presence of U.S. troops in Muslim countries. U.S. troops' deployment in Muslim countries creates a negative feeling toward the U.S. Media coverage of those sentiments in the U.S. media drastically affects U.S. aid volume, not directly related to U.S. national interests (S. Kim, 2013).

1.3. Data and Empirical Strategy:

For our data analysis, we used bilateral development aid commitment and disbursement and humanitarian and food aid disbursement. The primary source of this aid information is the OECD's Development Assistance Committee (DAC). Foreign aid data valued in constant 2010 U.S. dollars. We collected ODA commitments and disbursements between 1966 and 2014. The DAC started recording humanitarian aid data in 1995 and food aid in 1975. Data on humanitarian assistance range from 1995 to 2014, and food aid is between 1975 and 2014. The data on ODA commitments and disbursements dates to 1960.

However, some variables had insufficient/missing observations for some country groups. We failed to match these inconsistencies with the Center for Research on the Epidemiology of Disasters (CRED) database. We dropped those country-specific inconsistent observations. DAC maintains a list of ODA recipients; Appendix Table 1A3 shows that list. Table 1A3. So based on the inconsistency criteria, we selected 134 countries for our data collection purpose. Dependent variables of our analysis are US ODA commitments and disbursements and humanitarian and food aid disbursements.

Newspaper citation is our independent variable of interest. We defined Stories published in the U.S. newspapers related to a non-US country event as citations in our analysis. The citation data was obtained from four U.S. frontline newspapers, The Wall Street Journal, The New York Times, The Los Angeles Times, and The Washington Post. Digital newspaper archive ProQuest is sought for these citations. Appendix Table 1A2 provides the list of ProQuest newspaper archives. We came across various types of media variables while reviewing the literature. The media variables synopsis from the literature is listed in appendix Table 1A1. Generally, non-US country and disaster news are predominantly used in the literature, either together or separately. Each country-event citation setting has a unique impact on aid. Hence, we disaggregated the citation into general news, disaster, and ODA news citations. The introduction of a three-tier citation is distinctive in the literature that can capture the media effect of aid in a broader spectrum.

Citation data collection processes are very complex and time intensive. We used the following steps to ensure the process was free from any potential error. ProQuest newspaper repository searches through keywords in selected newspapers. Three separate keyword search processes ran for the citation. We did not consider every possible type of newspaper content for our keyword search. We carefully consulted an extensive newspaper glossary[19] available on the web. The newspaper contents "general article," "editorial,"

[19] 1.http://ncpressfoundation.org/newspaper-terms/; 2. http://www.enchantedlearning.com/newspaper/glossary.shtml; 3. https://topofthefold.wordpress.com/2009/01/14/newspaper-journalism-glossary/

"letter to the editor," and "news article" on aid recipients are preferred purposively in the search.

We used the natural disaster definitions from CRED for our disaster citation search. And performed a combined search process using CRED's natural disaster categories. For example, "Geophysical: Earthquake," "Meteorological: Storm, Hurricane, Tornado, Typhoon," "Hydrological: Flood, Landslide, Tsunami," and "Climatological: Drought." Additional search terms like "Natural Calamity" and "Natural Disaster" were attached with the combined search to achieve better results. The appendix Table 1A4 shows the complete list of disasters. For the foreign aid citation, the keywords considered were "Foreign aid," "Foreign assistance," and "Official assistance." The general citation search process excluded keywords related to the disaster and aid citation.

Besides, the separation of citations will allow us to analyze U.S. responses to nations vulnerable to frequent disasters. For identification purposes each citation category will let us dissect the impact of each type on development aid. The identification strategy will further guide us in distinguishing the effect of media citations on humanitarian assistance and disbursements of food aid relative to development aid. We used a fixed-effect (F.E.) panel data technique for our data analysis. The F.E. model removes the aid's influence from time-invariant features. We can evaluate the net effect of the predictors, notably media variables, on the outcome variable (types of aid).

Evaluating the role of media and disaster characteristics on U.S. aid is the core of our control variable selection. The disaster variables related to controls are frequency of disaster, fatalities, people affected, and property damage in the afflicted country. The source of these disaster variables is CRED. The yearly disaster data would assess disaster vulnerability and trigger a country's exposure to U.S. newspapers. Our research aims to understand the role of other factors behind the U.S. aid disbursement. We considered the following control variables:

- Per capita GDP: GDP data comes from the World Bank and is in constant 2010 dollars.
- Population: Population figures are acquired from the database of the United Nations Population Division and are tallied annually in millions for each country.
- Trade: Trade is measured by the constant bilateral U.S. trade balance in 2010 dollars. The U.S. Census Bureau is the source of these numbers.
- U.S. friend in U.N.: Eric Voeten[20] compiled the database, and we extracted it from the Harvard University data repository. These variable records votes by an ally in favor of the U.S. at the U.N. General Assembly.
- Regime type: This variable uses a 21-point scale to assess the various regime types in a country. The scale ranges from -10 (heredity monarchy) to +10 (solid democracy). The original information came from the Center for Systemic Peace's (CSP) Polity IV study. We recoded them into three categories: dictatorship/autocratic (-10 to -6), managed democracy (-5 to +5), and democracy (+6 to +10).

[20] Please visit Voeten et al. (2009) for further understanding of this database.

- House majority: We gather this historical data from the U.S. House of Representatives website[21]. We recorded the House majority between the 89th and 113th Congress.
- Senate majority: The source of this data is the U.S. Senate website[22]. We looked at the Senate majority between 1966 to 2014.

Table 1.1 Summary statistic

	N	Mean	SD	Min.	Max.
US ODA commitments ($millions)	6566	1213.27	1199.45	0	3674
US ODA disbursements ($millions)	6566	75.364	314.197	-593.64	13599
General news citations	6566	438.43	1329.15	0	24381
Disaster news citations	6566	33.381	95.221	0	3027
ODA news citations	6566	15.67	30.787	0	602
Per Capita GDP ($)	6566	2299.35	2828.89	0	20333
Population (millions)	6566	30.315	125.83	0	1360
US bilateral trade balance ($millions)	6566	-1026.5	11852.7	-343000	16461
Natural disasters	6566	1.653	2.423	0	10
Natural disaster fatalities	6566	391.401	6723.39	0	30031
People affected	6566	708000	7980000	0	2.55e+
Disaster damage	6566	151000	1890000	0	1.10e+
US friend in UN	6566	.178	.465	0	36
Regime type	6566	1.936	0.724	1	3

Table 1.1 displays the summary statistics for our data. The mean US ODA commitments ($1213.27 million) are about 16 times bigger than the ODA disbursements ($75.364 million). The mean per capita ODA disbursement ($2.50) is lower than the mean per capita commitments ($48). This wide gap between them implies that the U.S., on average, commits more than it can disburse. Hudson (2013) estimated that only 60% of aid recipients were within 15% of expected disbursements in 2010, and 27% were within 5%. The payout is "widely" distinct from the volume of commitments rendered by beneficiaries that do not follow essential bureaucratic criteria for resource safeguards, unnecessary

[21] https://history.house.gov/Institution/Party-Divisions/Party-Divisions/

[22] https://www.senate.gov/history/partydiv.htm

delays in aid bureaucracy, and cumbersome donor sanction and distribution systems (Celasun & Walliser, 2008).

A country-specific general news citations (438.43 counts) are 1213% larger than disaster news citations (33.381 counts). The number of ODA news citations (15.67 counts) is approximately 96% smaller than that of the general news citations (438.43 counts); there are noticeable variations between the two sources.

A given unspecified disaster can kill about 236 (on average) people, about 4,28,312 people are affected, and approximately $92,000 worth of physical assets destroyed. The mean per capita GDP and mean bilateral trade balances may significantly affect aid commitments (disbursements), but we cannot conclude anything unless we estimate our data. The appendix Tables IA2-IA6 contain a full explanation of the data and variables.

Table 1.2 Correlations between each citation category's aid per capita commitments and capita disbursement.

Variables	ODA commitments	ODA disbursement	General news citations	Disaster news citations	ODA news citations
ODA commitments	1.000				
ODA disbursement	0.598	1.000			
General news citations	0.278	0.207	1.000		
Disaster news citations	0.212	0.223	0.345	1.000	
ODA news citations	0.158	0.112	0.530	0.259	1.000

Table 1.2 shows the correlation between per capita ODA commitments (disbursements) and citation types. The above table revealed no strong relationship between commitments (disbursements) and citations. Besides, there is proof of a weaker correlation between the citations. Only the ODA news citation demonstrates a moderate relationship with the general news citations, but it does not concern our analysis.

We assume that the following level and per capita F.E. panel data model is the most reasonable specification to estimate the effect of newspaper citations on any U.S. aid commitments or disbursements:

$$LY_{i,t} = \beta_0+\beta_1 LCitGen_{i.t} + \beta_2 LCitDis_{i.t} + \beta_3 LCitOda_{i.t}+ \Upsilon_i LX_{i,t} + \delta_1 Ldisasterno_{it} + \delta_2 Ltotaldeaths_{i,t} + \delta_3 Ltotalaffected_{i,t} + \delta_4 Ltdamage_{i,t} + \mathcal{E}_{i,t} \quad --(1)$$

$$LPY_{i,t} = \beta_0+\beta_1 LPCitGen_{i.t} + \beta_2 LPCitDis_{i.t} + \beta_3 LPCitOda_{i.t}+ \Upsilon_i LX_{i,t} + \delta_1 Ldisasterno_{it} + \delta_2 Ltotaldeaths_{i,t} + \delta_3 Ltotalaffected_{i,t} + \delta_4 Ltdamage_{i,t} + \mathcal{E}_{i,t} \quad --(1a)$$

The variables with notation *L* stand for Log, and *L.P.* indicates Log per capita. We denote the dependent variable by *Y*. The dependent variables are designated as $ODAcom_{i,t}$, $ODAdisb_{i,t}$, $FoodAid_{i,t}$, $AidHum_{i,t}$, are ODA commitments, ODA disbursements, food aid disbursements, and humanitarian aid disbursement, respectively, for country i in year t. The explanatory variables, $CitGen_{i,t}$, $CitDis_{i,t}$ and $CitOda_{i,t}$, are labeled as general, disaster, and ODA-related news citations, correspondingly, for a county i in year t. The appendix Table 1A5 further clarifies the variable used in our analysis.

The explanatory variable $X_{i,t}$ specifies control variables; namely, $PGDP$ is per capita real GDP, $trade$ is U.S. bilateral trade balance, and $population$. The control variables related to natural disasters are $disasterno$ is the frequency of disasters; $totaldeaths$ is fatality number; $totalaffected$ is the number of affected people and $tdamage$ records value of non-US property damaged during disasters. $Freedom$ measures the U.S.'s aid allocation response based on a regime that prevailed in a country i in period t. $Polity$ denote the status of prevailing democracy in a county i in the year t.

Some variables have no observations in some years in our data set, while others have negative values. To tackle the methodological issues, we transformed those variables monotonically using the Log of (1+observation=0) or Log of (lowest value + value of the variable of interest). The monotonic transformation performed in the data did not alter the order of the data set. The appendix Table 1A6 explains the monotonic transformation and the cutoff for each variable.

Our coefficients of interest are β_1, β_2, and β_3, which capture the impact of specific newspaper citations on aid types. These coefficients' significance enables us to infer whether the newspaper-foreign aid nexus is robust and would support our initial model identification. The insignificance of these coefficients and other significant coefficients of the controls would reinforce that those media citations are not crucial in aid jargon.

1.4. Aggregate Results:

<u>1.4.1.A. ODA Commitments and Disbursements: U.S.'s Reaction to Newspaper Citations.</u>

We began analyzing the impact of news citations on bilateral ODA commitments (disbursements) in Table 1.3 and presume independent variables are exogenous to aid. We did not regulate the country and year fixed effects in column (1) for ODA commitments. Each citation type has a positive and meaningful impact on ODA commitments in column (1) in an uncontrolled environment. The contribution of natural disaster news to ODA commitments is about 0.230 percent, which is more stable than the other two forms of citations.

The per capita GDP (PGDP) is a marker of the economic strength of a country. The PGDP elasticity of aid is 0.20, implying that the U.S. will help countries achieve extensive growth. We expect a development partner like the U.S. will provide further developmental contributions to a nation with a higher population (0.091) and a country vulnerable to

Table 1.3. Panel Fixed Effects Estimation: Dependent Variable: Log of ODA commitments (column 1-4) and Log of ODA disbursements (column 5-8) 1966 to 2014.

	(1) ODA commitments	(2) ODA commitments	(3) ODA commitments	(4) ODA commitments	(5) ODA disbursements	(6) ODA disbursements	(7) ODA disbursements	(8) ODA disbursements
General news citations	0.078***	0.037	0.040	0.013	0.008***	0.011***	-0.002	0.010
	(0.023)	(0.023)	(0.064)	(0.069)	(0.002)	(0.002)	(0.006)	(0.006)
Disaster news citations	0.230***	0.068*	0.220***	0.161*	0.007***	0.012***	-0.002	0.010
	(0.035)	(0.036)	(0.080)	(0.086)	(0.003)	(0.003)	(0.010)	(0.011)
ODA news citations	0.095***	0.223***	0.077	0.213**	0.021***	0.028***	0.037***	0.047***
	(0.036)	(0.036)	(0.097)	(0.100)	(0.003)	(0.003)	(0.013)	(0.013)
Per Capita GDP	0.199***	0.120***	0.232***	0.146***	-0.003***	-0.002*	0.001	0.006*
	(0.012)	(0.013)	(0.045)	(0.048)	(0.001)	(0.001)	(0.003)	(0.003)
Bilateral trade balance	0.144	0.196	-0.566***	-0.509***	0.034**	0.045***	-0.011**	-0.001
	(0.195)	(0.187)	(0.044)	(0.044)	(0.015)	(0.015)	(0.005)	(0.004)
Population	0.091**	0.120***	1.694***	0.180	0.025***	0.016***	0.055	0.093*
	(0.036)	(0.035)	(0.342)	(0.547)	(0.003)	(0.003)	(0.039)	(0.055)
Natural disasters	0.265***	0.140	0.206**	0.139	-0.003	-0.001	-0.001	0.005
	(0.102)	(0.099)	(0.082)	(0.085)	(0.008)	(0.008)	(0.009)	(0.010)
Natural disaster fatalities	0.027	0.062**	-0.073***	-0.040	0.006***	0.009***	0.002	0.003
	(0.026)	(0.025)	(0.026)	(0.025)	(0.002)	(0.002)	(0.003)	(0.003)
People affected	0.062***	0.046***	0.017	0.011	0.001	0.000	0.002	0.000
	(0.017)	(0.016)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)	(0.001)
Disaster damage	-0.068***	-0.059***	0.019	0.012	-0.006***	-0.005***	-0.004***	-0.003**
	(0.010)	(0.010)	(0.012)	(0.011)	(0.001)	(0.001)	(0.001)	(0.001)
US friend in UN	5.927***	7.329***	5.003***	5.164***	0.144***	0.126***	0.129***	0.129***
	(0.291)	(0.308)	(1.193)	(1.382)	(0.023)	(0.024)	(0.043)	(0.047)
Anocracy	-0.826***	-1.028***	-0.792***	-0.863***	0.046***	0.044***	0.055*	0.060**
	(0.083)	(0.082)	(0.234)	(0.235)	(0.006)	(0.007)	(0.030)	(0.028)
Democracy	0.046	-0.182*	-0.165	-0.401	0.014*	0.006	0.036	0.044*
	(0.099)	(0.097)	(0.290)	(0.294)	(0.008)	(0.008)	(0.028)	(0.026)
Observations	6566	6566	6566	6566	6566	6566	6566	6566
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

At a 1%, 5%, and 10% level, ***, **, and * are used to signify statistical significance. The standard errors of a panel fixed effects regression model are shown in parentheses for each nation. Log US ODA commitments and disbursement in $million in 2010 are dependent variables. ' For independent variables, the logarithmic form is employed.

natural hazards (0.265). A weak democratic government would face a decrease (-0.826 percent) in ODA commitments. A long-time U.S. ally would receive more assurance (5.93 percent) of US ODA. Again, the US ODA contribution would climb when more people fell victim to catastrophe, and we did not control the year and country-fixed effects.

The citations related to disaster significantly affect ODA commitments in Columns (2) and (3) as we impose country and year fixed effects, respectively. The variables PGDP, population size, U.S. friends at the U.N., and an anocratic nation status was vital for the United States' ODA commitments. The number of deaths in a natural catastrophe often influences ODA commitments, raises ODA by 0.062% as we enforce year fixed effects but reduces ODA by 0.073% as we control country fixed effects.

This result has exciting implications. An increase in ODA commitments because of controlled year fixed effects means U.S. development aid plans are independent of surprise shocks. In contrast, reducing the ODA commitments due to the country-fixed impacts is ambiguous. Finally, the year and country fixed effects are controlled in column (4) to obtain the net results of the media effect. As a result, the Disaster news and ODA news citations showed a favorable response to ODA promises.

The exposure to disaster or aid needed to push the development agenda immensely motivates the U.S. foreign aid commitments toward any country. This pledge implies that U.S. politicians see a non-US country's needs in the U.S. newspapers and are encouraged to donate more. Besides newspaper citations' influence, the U.S. promises more aid for its allies and lowers its aid quota for countries with illegitimate governments. The coefficients of general new citations from column (2) to column (4) indicate that additional news publications did not guarantee more US ODA commitments.

The ODA disbursements are sensitive to newspaper citations' coefficients with no control over the country and year fixed effects in column (5) and year fixed effects controlled in column (6). The results from columns (5) and (6) indicate that the U.S. disbursed more development aid to their trading partners. The PGDP coefficient sign is negative in both the columns, meaning countries with improved PGDP received less ODA from the U.S. An exciting discovery is that the U.S. heavily disburses aid to countries with a democratic regime.

The review from column (8) is most relevant for our investigation into newspaper citations on ODA disbursements. None of the coefficients disaster news citations was statistically significant (not even in column 7). In the previous research, disaster news is a dominant determinant of ODA disbursement (Drury et al., 2005; Eisensee & Strömberg, 2007; Moeller, 2010; Olsen et al., 2003; Potter & Van Belle, 2004). Instead, we found that ODA-related reports (0.047 percent) are essential in US ODA disbursements.

There are many implications for the findings from Table 1.3; first, variables such as PGDP, U.S. friend to the U.N., and population are crucial determinants of US ODA, especially for disbursement. Second, the influence of media citations on ODA policies is less significant than that of other academics. Third, the U.S. continues to fund non-democratic countries.

1.4.1.B. Per Capita ODA Commitments and Disbursements: U.S. Reaction to Newspaper Citations.

The previous subsection found that only ODA-related news significantly affected ODA disbursements, while disaster citations and ODA news impacted the ODA commitments. We extended our analysis using the per capita estimations in Table 1.4.

Continuing the same partial significance pattern will imply that media citations have a weaker impact on ODA commitments and disbursements than a robust relationship suggested by the previous research (Van Belle, 2000).

We initially compared ODA commitments (in column 1) and disbursements (in column 5). Each type of media citation in both columns significantly affects ODA commitments and disbursements when not controlled for any fixed effect. The general news citation relatively had the most impact (0.13 percent) on ODA commitments than disbursements (0.033 percent), whereas the disaster news impact was weakest (0.076 percent vs. 0.017 percent) on the US ODA.

Our analysis from column (1) suggests a positive change in the PGDP increases ODA commitments. According to the aid literature, increasing ODA allocation enhances per capita GDP (Hailat & Magableh, 2018; Nowak-Lehmann et al., 2012). The U.S. vested interests in global geo-policy and generously committed (5.1%) more than disbursed (0.92 percent) ODA to its allies. The number of disaster-affected people also influenced US ODA policy.

When pledging ODA for non-democratic nations, the United States promised to pay less but paid more because well-focused aid for democracy significantly influenced democratization (Scott et al., 2020). Columns (2) and (5) only point to regressions results for the year fixed effects. Each citation significantly affected the US ODA disbursements in column (5). In column (2), neither the disasters nor ODA newspaper citations had a decisive impact on ODA commitments.

Table 1.4. Fixed Effects on the Panels Estimation: ODA commitment (column 1-4) and disbursement (column 5-8) logs from 1966 to 2014 are the dependent variables in this study.

	(1) ODA commitments	(2) ODA commitments	(3) ODA commitments	(4) ODA commitments	(5) ODA disbursements	(6) ODA disbursements	(7) ODA disbursements	(8) ODA disbursements
General news citations	0.131***	0.054**	0.143**	0.094	0.033***	0.032***	0.013	0.017
	(0.022)	(0.022)	(0.060)	(0.064)	(0.003)	(0.003)	(0.013)	(0.012)
Disaster news citations	0.084***	-0.020	0.086	-0.009	0.017***	0.012**	0.028	0.027
	(0.032)	(0.032)	(0.073)	(0.079)	(0.005)	(0.005)	(0.017)	(0.018)
ODA news citations	0.076**	0.149***	0.025	0.088	0.064***	0.071***	0.025	0.027
	(0.038)	(0.038)	(0.077)	(0.072)	(0.006)	(0.006)	(0.027)	(0.027)
Per Capita GDP	0.202***	0.133***	0.238***	0.159***	0.002	-0.003	0.019**	0.017**
	(0.011)	(0.011)	(0.044)	(0.048)	(0.002)	(0.002)	(0.008)	(0.008)
Bilateral trade balance	0.006	0.060	0.468**	0.422**	0.150***	0.167***	0.065	0.078
	(0.252)	(0.243)	(0.194)	(0.203)	(0.039)	(0.039)	(0.073)	(0.070)
Population	-0.555***	-0.614***	0.554**	-0.810	-0.017***	-0.019***	-0.012	-0.011
	(0.029)	(0.028)	(0.269)	(0.682)	(0.004)	(0.004)	(0.041)	(0.076)
Natural disasters	0.227**	0.115	0.175**	0.115	-0.036**	-0.043***	-0.012	-0.012
	(0.090)	(0.088)	(0.072)	(0.077)	(0.014)	(0.014)	(0.011)	(0.012)
Natural disaster fatalities	0.012	0.041*	-0.054***	-0.028	0.009**	0.013***	0.002	0.005*
	(0.023)	(0.023)	(0.020)	(0.020)	(0.004)	(0.004)	(0.003)	(0.003)
People affected	0.045***	0.030**	0.012	0.007	0.004*	0.002	0.003**	0.001
	(0.015)	(0.014)	(0.010)	(0.011)	(0.002)	(0.002)	(0.001)	(0.001)
Disaster damage	-0.050***	-0.042***	0.009	0.004	-0.005***	-0.003**	-0.005***	-0.004***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)
US friend in UN	5.113***	6.724***	4.795***	5.372***	0.918***	1.080***	0.786**	0.918**
	(0.255)	(0.274)	(1.249)	(1.520)	(0.040)	(0.044)	(0.326)	(0.374)
Anocracy	-0.699***	-0.837***	-0.564***	-0.579***	0.085***	0.080***	0.063**	0.071**
	(0.073)	(0.073)	(0.191)	(0.195)	(0.011)	(0.012)	(0.030)	(0.029)
Democracy	0.013	-0.194**	-0.036	-0.206	0.033**	0.018	0.061**	0.062**
	(0.086)	(0.085)	(0.237)	(0.248)	(0.013)	(0.014)	(0.025)	(0.029)
Observations	6566	6566	6566	6566	6566	6566	6566	6566
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

At a 1%, 5%, and 10% level, ***, **, and * are used to signify statistical significance. The standard errors of a panel fixed effects regression model are shown in parentheses for each nation. Log US ODA commitments and disbursement in $million in 2010 are dependent variables. [a] For independent variables, the logarithmic form is employed.

We regulate columns (3) and (7) regressions for country-fixed effects. No newspaper variables increased US ODA disbursement in column (7), but the general news category influenced commitments. The U.S. allies' UN-voting preference in favor of the

U.S. increased ODA commitments and disbursement consistently in columns (3) and (7). Our study's most important contribution is that we deduced newspaper citations are not a significant determinant of ODA commitments; rather, newspaper publications significantly influence disbursements.

We rechecked those statements in columns (4) and (8). The net results showed no citation impact once we adjusted those columns for year and country fixed effects. We also found variables such as per capita GDP, democracy, and U.S. friends in the U.N. have a stimulating impact on US ODA commitments or disbursement. The factors related to natural disasters did not affect ODA commitments. We suspected that the disaster variables are post-engagement shocks, so the U.S. inclination to award aid is more of a disburse decision.

The fatalities in column (8) showed increased ODA disbursement by 0.05 percent during any disaster. A mutual trade partner of the United States receives 0.422 percent more ODA commitments than a non-US non-trading nation. However, this promise did not result in further ODA distribution.

To infer whether media reaction is one of the critical determinants of US ODA commitment or disbursements, we need further investigation into the other forms of aid before reaching any conclusion. Therefore, we will explore the media's impact on humanitarian and food assistance in the next section.

1.4.2.A. Humanitarian Aid: The Role of Newspaper Citations on The U.S. Disbursements.

After a violent war, a tragedy, or a natural calamity, humanitarian intervention helps rescue people, relieve misery, and preserve human rights (Humanitarian Assistance -

Table 1.5. Panel Fixed Effects Estimation: Dependent Variable: Log of humanitarian aid disbursement (column 1-4) and Log of per capita humanitarian aid disbursements (column 5-8) 1995 to 2014.

	(1) Humanitarian disbursement	(2) Humanitarian disbursement	(3) Humanitarian disbursement	(4) Humanitarian disbursement	(5) Humanitarian disbursement	(6) Humanitarian disbursement	(7) Humanitarian disbursement	(8) Humanitarian disbursement
General news citations	0.067***	0.065***	0.139***	0.162***				
	(0.018)	(0.016)	(0.052)	(0.054)				
Disaster news citations	0.048*	-0.004	0.172***	0.186***				
	(0.027)	(0.025)	(0.048)	(0.055)				
ODA news citations	0.115***	0.250***	0.141***	0.138***				
	(0.028)	(0.028)	(0.049)	(0.049)				
Per Capita GDP	-0.110***	-0.154***	0.015	-0.015	-0.047***	-0.062***	0.032*	0.019
	(0.015)	(0.014)	(0.034)	(0.038)	(0.007)	(0.007)	(0.018)	(0.021)
Bilateral trade balance	0.162	0.225**	-0.002	-0.004				
	(0.099)	(0.092)	(0.011)	(0.016)				
Population	0.053*	-0.023	4.911***	4.444***	0.025**	0.015	1.605***	1.297***
	(0.030)	(0.029)	(0.572)	(0.753)	(0.013)	(0.012)	(0.270)	(0.414)
Natural disasters	-0.069	-0.038	0.047	0.002	0.000	0.015	0.013	-0.003
	(0.072)	(0.068)	(0.061)	(0.056)	(0.034)	(0.033)	(0.030)	(0.030)
Natural disaster fatalities	0.045**	0.087***	0.002	0.011	0.016*	0.031***	0.006	0.010
	(0.019)	(0.018)	(0.016)	(0.015)	(0.009)	(0.009)	(0.009)	(0.009)
People affected	0.026**	0.007	-0.007	-0.007	0.006	-0.002	-0.002	-0.002
	(0.013)	(0.012)	(0.009)	(0.009)	(0.006)	(0.006)	(0.005)	(0.005)
Disaster damage	-0.025***	-0.017***	0.003	0.005	-0.014***	-0.012***	-0.001	0.000
	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
US friend in UN	-1.291***	-0.084	-0.352	0.718*	-0.303**	0.152	0.029	0.509**
	(0.277)	(0.283)	(0.356)	(0.403)	(0.134)	(0.141)	(0.230)	(0.242)
Anocracy	0.195**	0.014	0.064	0.012	0.076*	0.017	0.118	0.096
	(0.081)	(0.076)	(0.304)	(0.304)	(0.039)	(0.038)	(0.139)	(0.139)
Democracy	-0.023	-0.224***	0.077	-0.014	0.010	-0.057	0.187	0.138
	(0.086)	(0.081)	(0.324)	(0.327)	(0.041)	(0.039)	(0.147)	(0.147)
		(0.155)		(0.172)		(0.076)		(0.113)
P. General news citations					0.037***	0.031***	0.099***	0.106***
					(0.009)	(0.009)	(0.032)	(0.033)
P. Disaster news citations					-0.003	-0.014	0.044*	0.045*
					(0.013)	(0.013)	(0.023)	(0.023)
P. ODA news citations					0.078***	0.114***	0.049**	0.052***
					(0.017)	(0.016)	(0.019)	(0.019)
P. Bilateral trade balance					-0.059	-0.066	0.048	0.056*
					(0.069)	(0.067)	(0.034)	(0.032)
Observations	2680	2680	2680	2680	2680	2680	2680	2680
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Panel fixed effects regression model with standard errors, clustered at the country level, in parentheses. Dependent variables are log US humanitarian aid disbursements commitments and log per capita humanitarian aid disbursements valued in 2010 million dollars. Independent variables are in log level and log per capita form. Independent variables labelled as P. are in per capita term.

(OECD, n.d.). It is essential to determine the role of media in U.S. humanitarian aid distribution, and we extended our analysis for that purpose in Table 1.5. We compared the outcome of our investigation in log levels in columns 1-4 and log per capita terms in columns 5-8.

In column (4) of Table 1.5, we controlled both the year and the country fixed effects. Our estimation reveals that newspaper citations were essential to disbursing U.S. humanitarian aid. The disaster news alone increased 0.186 percent of U.S. humanitarian aid. Again, the general category of news citation would increase by 0.162 percent of the disbursement. It also shows that newspaper material showcasing the ODA need of a recipient nation raises U.S. humanitarian assistance disbursement by 0.14 percent. The U.S. generously allocated more (4.44 percent) humanitarian aid when the affected country is densely populated. A country that is a historic U.S. partner in global geopolitical affairs earns 0.72 percent more in humanitarian assistance disbursement. We looked at the net increase in per capita humanitarian aid disbursement in column (8). All three newspaper citations increase the U.S. disbursement of humanitarian assistance like the log-level analysis results.

The general news category raises humanitarian aid per capita by 0.11 percent, and per capita disaster news per country accounts for a 0.045 percent increase. In contrast, the ODA news citation accounted for a 0.052 percent increase in assistance. The significant news citations reiterate that the linkage between newspaper citations and U.S. foreign aid is more applicable in humanitarian aid than the ODA commitment or disbursement. Finally, the positive per capita bilateral trade balance hinted that the U.S. would increase humanitarian assistance toward its trading partners when a sudden calamity hits them.

1.4.2.B. Food Aid: Role of Newspaper Citation on The Us Disbursements.

Food assistance operates similarly to the ODA, and donors widely use three categories. Food aid is a balance of payment transfer (BOP) or budgetary support. Project food aid for hunger-relief programs and relief food aid for victims of natural or man-made disasters that are targeted and freely distributed (Food aid—OECD, n. d.). Preventing disasters is the primary aim of food assistance delivery. Table 1.6 looked at the effect of newspaper citations on food assistance based on the level and per capita distribution of food aid from 1975 to 2014. , The disbursement of food assistance is not profoundly linked to natural disasters.

We controlled the country and year-fixed effects in column (4). Disaster and general news coverage had little effect on food aid. The aid-related news mentioned raises the payment of U.S. food assistance by 0.020%. We think this rise is due to the humanitarian support needed to feed impacted individuals during an emergency. Recipients' healthy diplomatic relationship with the U.S. also played a vital role in column (4) to disburse U.S. food aid.

We controlled the country and year fixed effects in the per capita regression in column (8). Each type of newspaper citation significantly influenced the U.S. per capita food aid disbursement. We found that each newspaper news positively increases food aid by approximately 0.02 percent, and the general news category has the most decisive impact among the citations. Similar to our previous section's analysis, the U.S. has continued distributing more (0.186 percent) food aid to its allies and countries with an upward trend in PGDP (0.014 percent).

Table 1.6. Panel Fixed Effects Estimation: Dependent Variable: Log of food aid disbursement (column 1-4) and Log of per capita food aid disbursements (column 5-8) 1975 to 2014.

	(1) Food aid disbursement	(2) Food aid disbursement	(3) Food aid disbursement	(4) Food aid disbursement	(5) Food aid disbursement	(6) Food aid disbursement	(7) Food aid disbursement	(8) Food aid disbursement
General news citations	-0.002	0.000	0.001	0.005				
	(0.002)	(0.002)	(0.004)	(0.005)				
Disaster news citations	-0.012***	-0.004	-0.007	-0.004				
	(0.003)	(0.003)	(0.007)	(0.007)				
ODA news citations	0.030***	0.025***	0.022***	0.020***				
	(0.003)	(0.003)	(0.004)	(0.004)				
Per Capita GDP	-0.001	0.003***	0.005**	0.010***	0.002	0.008***	0.002	0.014***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Bilateral trade balance	0.031**	0.024	-0.002	-0.006**				
	(0.016)	(0.016)	(0.002)	(0.002)				
Population	0.007**	0.006*	-0.174***	-0.060	-0.031***	-0.026***	-0.238***	0.065
	(0.003)	(0.003)	(0.062)	(0.044)	(0.004)	(0.004)	(0.067)	(0.062)
Natural disasters	-0.018**	-0.011	0.006	0.009	-0.013	-0.002	0.002	0.010
	(0.009)	(0.009)	(0.007)	(0.007)	(0.013)	(0.013)	(0.010)	(0.009)
Natural disaster fatalities	0.008***	0.008***	0.001	0.001	0.006*	0.005	-0.000	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
People affected	0.002	0.003**	-0.001	-0.001	0.001	0.003	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Disaster damage	-0.000	-0.001	-0.001	-0.000	-0.001	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
US friend in UN	0.090***	0.147***	-0.012	0.083**	0.080*	0.156***	0.022	0.186**
	(0.029)	(0.031)	(0.025)	(0.040)	(0.042)	(0.045)	(0.047)	(0.092)
Anocracy	-0.013*	0.020***	0.011	0.029	-0.104***	-0.057***	-0.049*	-0.013
	(0.008)	(0.008)	(0.019)	(0.020)	(0.011)	(0.011)	(0.027)	(0.025)
Democracy	0.014	0.045***	0.009	0.039	-0.042***	0.007	-0.065	0.002
	(0.009)	(0.009)	(0.027)	(0.030)	(0.013)	(0.013)	(0.041)	(0.041)
P.General news citations					-0.004	-0.000	0.016**	0.021***
					(0.003)	(0.003)	(0.008)	(0.008)
P.Disaster news citations					-0.013***	-0.006	0.005	0.017**
					(0.005)	(0.005)	(0.007)	(0.008)
P.ODA news citations					0.046***	0.034***	0.028***	0.018*
					(0.006)	(0.006)	(0.010)	(0.010)
P.Bilateral trade balance					-0.015	-0.023	-0.011	0.010
					(0.034)	(0.033)	(0.032)	(0.018)
Observations	5360	5360	5360	5360	5360	5360	5360	5360
Country FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes

At a 1%, 5%, and 10% level, ***, **, and * are used to signify statistical significance. The standard errors of a panel fixed effects regression model are shown in parentheses for each nation. Log US food aid and per capita, food aid disbursement of $million in 2010 are dependent variables. Independent variables are in log level and log per capita form. Independent variables labeled as P. are in per capita terms.

1.4.3.1 Comparative Evaluations Between the Type of Aid: Scenario Food Aid Disbursement.

Table 1.7 compared the consequence of media citations across US ODA and food aid allocations. We matched the ODA data period with the food aid data period of 1975-2014 for the comparative analysis. In the level form of examination in column (3), we could not find a single newspaper citation that markedly changed the food aid disbursement pattern. Still, in per capita analysis in column (6), all forms of mention emerged as significant contributors.

We tested the effect of newspaper citations on ODA commitments (disbursements) in level forms in columns 1-2 and per capita forms in columns 4-5. In the next step, we tried to equate the results with food aid disbursements. The ODA commitments in the level form increased by all three news citations, general news by 0.071 percent, disaster news by 0.109 percent, and ODA news quotes by 0.109 percent, respectively. With the ODA disbursements analysis in levels, a one percent increase in the general news category increases ODA disbursements by 0.010 percent. Neither the disaster nor ODA in the news category impacts U.S. food aid disbursements at the level.

Our comparative results dramatically changed in per capita form. Food aid disbursement responded to newspaper citations, whereas the media citations did not influence ODA disbursements. Finally, only the general news category robustly affected US ODA commitments in per capita forms. Comparing food aid to ODA shows that the media significantly influences U.S. food aid allocations.

Table 1.7. Significance of newspaper citations between ODA and food aid disbursement. Panel Fixed Effects Estimation: Dependent Variables: Log Level form (column 1-3) and Log per capita form (column 4-6), from 1975 to 2014.

	(1) ODA commitments	(2) ODA disbursements	(3) Food aid disbursement	(4) ODA commitments	(5) ODA disbursements	(6) Food aid disbursement
General news citations	0.071**	0.010*	0.004			
	(0.032)	(0.005)	(0.003)			
Disaster news citations	0.109**	0.019	-0.005			
	(0.044)	(0.012)	(0.004)			
ODA news citations	0.184***	0.018***	0.020***			
	(0.042)	(0.006)	(0.004)			
P. General news citations				0.154**	0.012	0.021***
				(0.072)	(0.013)	(0.008)
P. Disaster news citations				-0.048	0.019	0.017**
				(0.083)	(0.020)	(0.008)
P. ODA news citations				0.074	0.029	0.018*
				(0.070)	(0.021)	(0.010)
Observations	5360	5360	5360	5360	5360	5360
R-Squared	.283	0.120	.010	0.237	0.152	0.141

At a 1%, 5%, and 10% level, ***, **, and * are used to signify statistical significance. The standard errors of a panel fixed effects regression model are shown in parentheses for each nation. Dependent variables column (1) to column (3) are in log level form, and column (4) to column (6) is in Log per capita form valued in 2010 million dollars. Independent variables labeled as P. are in per capita terms. We only report coefficients related to citations so the reader can follow them easily.

1.4.3.2 Comparative Evaluations Between the Aid: Scenario Humanitarian Aid Disbursement.

We took a sub-sample of ODA commitments and disbursements from 1995 to 2014 and compared them with U.S. humanitarian aid disbursements. We analyzed the data sets at the level and per capita forms and related the results in Table 1.8.

The findings from Table 1.8 have multiple implications. First, general news citations extensively affected ODA commitments in levels and per capita forms. Second, disaster news and general news substantially impacted ODA disbursement in both functional types. Third, the ODA-related information, for example, a country's need for ODA or a lobbying activity for ODA, had a broader impact on humanitarian aid disbursement (0.163%). Fourth, the U.S. humanitarian assistance is receptive to any types of newspaper citations in level and per capita analysis. Fifth, the per capita comparison result revealed that disaster news had no impact on ODA commitments and had little influence on humanitarian aid. Finally, ODA commitment (0.188) is far more significant than ODA disbursement (0.024). From a policy perspective, it implies as long a country's image is visible in the American newspapers, the U.S. will commit more aid.

Table 1.8. Comparison of disbursement between ODA and humanitarian aid Disbursements. Panel Fixed Effects Estimation: Dependent Variables: Log level form (column 1-3) and Log per capita form (column 4-6), from 1995 to 2014.

	(1) ODA commitments	(2) ODA disbursements	(3) Humanitarian disbursement	(4) ODA commitments	(5) ODA disbursements	(6) Humanitarian disbursement
General news citations	0.162***	0.022**	0.122***			
	(0.045)	(0.009)	(0.028)			
Disaster news citations	0.087*	0.024**	0.170***			
	(0.052)	(0.011)	(0.034)			
ODA news citations	-0.027	0.008	0.163***			
	(0.052)	(0.006)	(0.034)			
P. General news citations				0.188**	0.024**	0.106***
				(0.087)	(0.012)	(0.033)
P. Disaster news citations				0.081	0.019*	0.045*
				(0.063)	(0.011)	(0.023)
P. ODA news citations				-0.000	0.008	0.052***
				(0.060)	(0.006)	(0.019)
Observations	2680	2680	2680	2680	2680	2680
R-Squared	0.13	0.231	0.24	0.100	0.110	0.150

At a 1%, 5%, and 10% level, ***, **, and * are used to signify statistical significance. The standard errors of a panel fixed effects regression model are shown in parentheses for each nation. Dependent variables column (1) to column (3) are in log level form, and column (4) to column (6) is in Log per capita form valued in 2010 million dollars. Independent variables labeled as P. are in per capita terms. We only report coefficients related to citations so the reader can follow them easily.

1.4.4. A Comparative Scenario: Role of The Us House and Senate Majority on ODA Allocation.

Foreign aid allocation is a public policy decision. This major policy decision-making requires the approval of key policy stakeholders, the U.S. House of Representatives, and Senate members. The connection between media and foreign policy is indirect. A general belief is that the media influenced foreign policy officials via an agenda-setting mechanism. The literature points out that their relationship is mixed. C. Zhang & Meadows III (2012) found a negative connection between the press coverage, public documents released by the president, and popular opinion. According to an agenda-setting assessment, foreign affairs' prominence in the media is strongly linked to the public's interest in foreign affairs (Soroka, 2003).

Our analysis so far generated the fact that newspaper citations profoundly affect the U.S.'s humanitarian assistance and food aid allocation. The newspaper's direct impact on development aid is ambiguous because the disbursement is entirely unresponsive, whereas some of the citations affect commitments to some extent. In this section, we extended our analysis from the policy stakeholders' point of view.

We think there is an interaction effect between the newspaper citations and policymakers' approval of foreign aid allocation decisions. We regress the interaction between the U.S. House of Representative majority on the ODA commitments and disbursement to check that relationship.

We also included the U.S. Senate majority in a similar estimation. Our objective is to clarify the indirect relationship between media and ODA, if that exists, with stakeholders' direct influence on ODA. We report the outcomes of that interaction effect in Table 1.9.

Column (1) and (2) presents the estimated results of ODA commitment and disbursements in level forms. We controlled the country and year fixed effects. Our primary goal is to examine whether media citations become relevant when the U.S. House of Representatives and Senate's influence on aid is considered. First, the ODA news citations impacted ODA disbursements, similar to what we observed when we did not control majorities in Table 1.3. Second, we saw disaster news as a significant determinant of ODA commitments regardless of their censored status.

Third, we detected a Republican Party majority in both the House and Senate increases the chances of U.S. development aid commitments to recipients. The ODA news stories immensely contribute to this positive outcome, which we predict due to foreign aid

Table 1.9. Significance of the House of Representatives and Senate majority on ODA commitments and disbursements. Panel Fixed Effects Estimation: Dependent Variables: Log level form (column 1-2) and Log per capita form (column 3-4), from 1966 to 2014.

	(1) ODA commitments	(2) ODA disbursements	(3) ODA commitments	(4) ODA disbursements
General news citations	0.016	0.011		
	(0.071)	(0.008)		
Disaster news citations	0.213**	0.011		
	(0.097)	(0.012)		
ODA news citations	0.136	0.054***		
	(0.107)	(0.014)		
Republican controlled House (RCH)	1.031*	-0.147**	1.422**	-0.136
	(0.603)	(0.060)	(0.680)	(0.092)
Republican controlled Senate (RCS)	0.607**	0.056*	0.439*	0.035
	(0.300)	(0.029)	(0.239)	(0.040)
RCH # General news citations	0.042	0.000		
	(0.096)	(0.005)		
RCS # General news citations	-0.037	-0.006		
	(0.063)	(0.005)		
RCH # Disaster news citations	-0.163	0.015		
	(0.155)	(0.011)		
RCS # Disaster news citations	-0.015	-0.014		
	(0.087)	(0.010)		
RCH # ODA news citations	0.230*	-0.022		
	(0.128)	(0.018)		
RCS # ODA news citations	0.029	0.000		
	(0.116)	(0.014)		
P. General news citations			0.096	0.006
			(0.070)	(0.016)
P. Disaster news citations			0.058	0.037**
			(0.090)	(0.015)
P. ODA news citations			0.060	0.017
			(0.099)	(0.045)
RCH # P. General news citations			-0.100	0.030
			(0.110)	(0.026)
RCS # P. General news citations			0.111	0.015
			(0.067)	(0.011)
RCH # P. Disaster news citations			-0.147	-0.050
			(0.162)	(0.032)
RCS # P. Disaster news citations			-0.021	0.013
			(0.115)	(0.027)
RCH # P. ODA news citations			0.240	0.086
			(0.212)	(0.065)
RCS # P. ODA news citations			-0.148	-0.036
			(0.128)	(0.033)
Observations	6566	6566	6566	6566

At a 1%, 5%, and 10% level, ***, **, and * are used to signify statistical significance. The standard errors of a panel fixed effects regression model are shown in parentheses for each nation. Dependent variables column (1) to column (2) are in log level form, and column (3) to column (4) is in Log per capita form valued in 2010 million dollars. Independent variables labeled as P. are in per capita terms. We report coefficients related to citations and the majority to allow the reader the follow.

lobbyists' strong ties with Republican Senators. Fourth, a counter-cyclical relation exists in ODA disbursement. A democratic minority in the House reduced it while a Republican majority in the Senate would raise it. Our results indicated no linkage between newspaper citations and the agenda of political representatives.

We presented the per capita form estimations in columns (3) and (4). The findings from per capita ODA commitments are quite the opposite of column (1) results. We could not locate a single newspaper citation with a strong influence on ODA commitments after regulating House and Senate majority effects. Not a single interaction term between newspaper citations and House/Senate majority supported the need for people's voice in the elected candidates' agenda.

But individually, each House and Senate majority increased the commitments in the past. The same pattern continued in the disbursement process. The state of majority in both Chambers did not affect the decision process, let alone newspaper stories influence them. The only omission from level form analysis in column (2) is that per capita disaster news stories influenced development aid's actual allocation.

1.5 Discussion and Policy Implication:

Here in this chapter, our investigation of the media-aid nexus delivers some insightful implications. There is an ongoing debate in the existing literature on the short-term vs. long-term effectiveness of media aid connections. The three new media variables postulated that the media effect, i.e., the role of a newspaper, is strongly felt in the short-term aid (food, humanitarian) and not so much in the long-term development aid.

This research of the media-aid nexus yields several critical conclusions. Existing research questions the relative usefulness of short-term and long-term media assistance linkages. The three new media variables hypothesized that the media impact, i.e., the function of a newspaper, is felt significantly in short-term assistance (food and humanitarian) but not in long-term development aid.

This difference in the denomination has exciting foundations. The factors that affect development aid allocation are difficult to change in the long-term pattern of the ODA allocation. For example, lobbying, agri-business, export, foreign direct investment, and strategic interest are locked in a donor's long-term interest. Humanitarian assistance and food aid do not have any such factors bounded. Hence media exposure could create more sympathy for the donors and aid disbursement. This paper is the first to provide this rationale and robust evidence.

Our findings also establish that media is one of the critical factors affecting US foreign aid allocation. Most of the research (Olsen et al., 2003; Potter & Van Belle, 2004; Strömberg, 2007; Van Belle, 2000) was conducted in the public policy and political science domain. Hence, previous authors did not investigate or account for the presence of endogeneity issues. We did not also account for endogeneity between the three media citations. This particular methodological concern is a significant limitation of this research that we plan to account for it in our subsequent research[23].

Another limitation of this paper is the absence of social media networks' influence on the short and long-term US foreign aid. Social media networks such as Facebook and Twitter provided a new avenue to evaluate the media's role in foreign aid allocation. There is evidence (Afzal et al., 2021; Ceccardi, 2020) that shows the role of social media on foreign aid dynamics. We initially planned on using historical tweets from 2007. But the

[23] We are working on a new methodology based on the seemingly unrelated regression equations (SURE) model to account for endogeneity between the media variables.

idea had to be shelved due to the funding limitation[24]. In our subsequent research, we intend to control the effect of social media using a dummy variable approach for each social media platform.

Bureaucracy is an important driver of foreign aid policy. Authors (Celasun & Walliser, 2008; Joly, 2014; Van Belle & Potter, 2011) showed that media and bureaucratic influence go hand in hand in designing aid-friendly policies. The media provides the space to reflect the recipient's need for aid. So, this research can give public policy makers a lucid picture of disaster-affected countries' short-term or crisis-dependent aid needs. Hence, policymakers can put more emphasis/weight on the media in their agenda-setting mechanism.

The impact of our disaster damage variable on aid was negative and significant, a major deviation from the existing literature (Eichenauer et al., 2020; Hallwright & Handmer, 2019; McLean & Whang, 2021; Wang et al., 2020) that states a positive effect. Hence, in our extended twin paper, we decided to add lag variables of past disaster damage and check whether it will alter our findings.

Given the limitations, this current chapter adds some value to the existing literature and for policymakers. First, for humanitarian aid allocation, policymakers can look at the media reflection to understand the need for aid for the affected countries. Second, development aid is unresponsive to media exposure; hence policymakers need not worry about media and disaster for the long-term aid policy design. Finally, our paper showed that crisis-based aid is always a media-dependent decision process.

[24] For example, market rate/quote for obtaining historical Twitter was as low as $100,000.

1.6 Conclusion:

The current research projects some new insights into the media-foreign aid research literature. We showed that the ODA disbursements in the extended period (1966-2014) had no connection with the newspaper coverages. Our result postulates that ODA commitments in level form respond to some news category, whereas per capita commitment analysis is utterly unresponsive to media variables. We performed a refined analysis with the US House and Senate majority data to crosscheck whether any natural association exists between ODA and newspaper citations. Based on this evidence, we could not convincingly demonstrate that news stories did matter for development aid in general. Hence, we think that media's net effect on ODA is ambiguous, while previously scholars (Drury et al., 2005; Eisensee & Strömberg, 2007; Potter & Van Belle, 2004; Van Belle & Hook, 2000) found it highly responsive to media variables.

From the comparative analytical point of view, we can convincingly conclude that humanitarian aid and food disbursement are always sensitive to media exposure. Country-specific news stories in the US newspapers significantly affected their disbursements. We also acknowledged that the research outcome differs by each researcher's method in their study.

One explanation for the ineffectiveness of ODA allocation through media citations is that the donor country's domestic interests directly affect foreign aid. Presidents must create assistance plans to garner majority support in Congress, and lawmakers don't randomly vote on aid; they react to the views of their voting constituencies, organize interest groups, and vote accordingly (Milner & Tingley, 2010).

ODA is partly captured by the donor country's economic and strategic objectives since it is institutionalized over a lengthy period. In contrast, humanitarian and food aid responses reflect short-term emergency assistance. Thus, our findings regarding the media's citation of the effectiveness of humanitarian aid allocation are justifiable.

Our most significant contribution to the literature is that we introduced a unique analysis of newspaper citations on aid based on the most extensive sample ever. We introduced three new media citations that can capture specific citations' impact on foreign aid. Finally, we provided evidence that the newspaper-aid nexus investigation is most relevant for humanitarian aid disbursement.

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Appendix:

Table 1A1. Summary of selected literature.

Paper title	**Dependent variable**	**Media variable source**	**Media variables**	**Donor in focus**	**Data period**
Simon (1997)	i) The sum of money sent by the American Red Cross. ii) US disaster aid.	i) The nightly news of the Vanderbilt Television News Archives.	i) The amount of time dedicated to the disaster in seconds. .	USA	1972-1990

Van Belle & Hook (2000)	ODA commitments	Vanderbilt Television News Archive (VTNA).	The annual number of news reports on the nation or its leader.	USA	1977-1992
Halton (2001)	NA	US/Canadian newspapers and television.	NA	USA, Canada	NA
Van Belle (2003)	ODA commitments.	i) VTNA. ii) The New York Times Index.	i) an annual number of news stories. ii) yearly number of news stories.	USA	1978-1991
Olsen et al.(2003)	Humanitarian assistance.	1. DR-TV and TV2 in Denmark 2. 23 leading UK, German, French, Italian, US, Spanish, and Danish newspapers.	Number of reports annually (newspaper or television)	USA, Europe	1998-2002

Table 1A1. Summary of selected literature (cont.)

Paper title	Dependent variable	Media variable source	Media variables	Donor in focus	Data period
Potter & Van Belle (2004)	ODA commitments	Asahi Shimbun a major Japanese daily.	1. Total news coverage measures how many Asahi articles mention the recipient country each year. 2. Negative coverage measures stories about Japan-related conflicts. 3. Unrest or coverage of violent political unrest. 4. Need includes articles about natural disasters, famine, and want. 5. Positive or neutral coverage was residual. Negative, unrest, and need-related coverage subtracted from total coverage.	Japan.	1986-1995
J.S.Kim (2005)	Five-year average ODA per capita.	i) Lexis Nexis Academic: Boston globe, Washington Post, and New York Times. ii) VTNA	i) Mean of natural hazard. ii) Mean epidemics. iii) Mean war. iv) Mean of natural disasters, epidemics, and war together.	USA	1970-1994

Table 1A1. Summary of selected literature (cont.)

Paper title	Dependent variable	Media variable source	Media variables	Donor in focus	Data period
Rioux & Van Belle (2005)	ODA commitments	French leading newspaper *Le Monde*.	Index Le Monde.	France.	1986-1998
Martin (2005)	ODA	NA	NA	Canada	Literature review
Strömberg (2007)	Disaster relief.	Major US television networks: ABC, CBS, NBC, CNN.	Disaster coverage in the news.	23 donor countries	1980-2004
Eisensee & Strömberg (2007)	Disaster relief.	The Vanderbilt Television News Archives.	Disaster coverage in the news from 2 to 40 days.	USA	1968-2002
Lim et al. (2008)	International assistance.	i) The LexisNexis ii) Factiva	Number of each country's news articles	159 countries.	1990-2000
Wei et al. (2009)	NA	SINA.com	The total number of daily news stories.	China	2003-2008
Van Belle (2009)	annual ODA commitments.	The New York Times	The number of stories published.	USA	1985-1995
Potter & Van Belle (2009)	Disaster aid commitments.	Asahi Shimbun, one of three major daily newspapers in Japan	The number of articles on each disaster event.	Japan and USA	1985-1998
Joye, 2010	NA	Top tier newspaper De Morgen and De Standaard. Second tier newspaper Het Nieuwsblad and Het Laatste Nieuws and Het Nieuwsblad.	Printed newspaper article on disaster situations.	Belgium.	1986-2006

Table 1A1. Summary of selected literature (cont.)

Paper title	Dependent variable	Media variable source	Media variables	Donor in focus	Data period
Moeller (2010)	Disaster aid	NA.	NA	NA	NA
Mason (2011)	Foreign aid.	Canadian Broadcasting Corporation (CBC).	Articles published online by the CBC news.	Canada	2010
Van Belle & Potter (2011b)	Emergency disaster assistance (cash or in-kind)	Japanese newspaper *Asahi Shimbun.*	The number of stories published.	Japan.	1985-1998
S. Kim (2013)	Economic assistance (loans/grants) from Greenbook.	New York Time index.	Yearly count of news stories associated with a Muslim country.	46 Muslim countries.	1990-2009
Joly (2014)	ODA commitments. Non-Bureaucratic ODA.	i) leading Belgian newspaper *De Standaard* ii) Two Flemish and two Walloon TV news archive.	i) Number of stories published. ii) Annual count of news stories.	Belgium	1995-2008
Becerra et al. (2014)	ODA total net disbursement.	Associated press archive.	Number of reports.	Multiple (44) donors.	1970-2008
Cawley (2015)	Overseas allocation.	Nexis database of US and UK newspapers.	Content analysis.	Ireland, UK, and USA	2008-2011
Joly (2016)	Emergency assistance.	Belgian leading newspaper *De Standaard*	i) count of yearly news stories. ii) Five yearly indices of annual news.	Belgium	2000-2008

Table 1A2. Subcategories of newspapers in the ProQuest Database

Sub-database Name	Coverage type	Timeline
The Christian Science Monitor	Local and regional news coverage.	1988 - current
Latin American News-stream	The Latin American News stream allows users to search for decades-long collections of the latest local, national and regional news material. It includes, in an active full-text format, newspapers, newswire, and news sites.	NA
ProQuest Historical Newspapers: Chicago Tribune	Historical news - newspaper articles	1894-1994
ProQuest Historical Newspapers: The Christian Science Monitor	Historical news - newspaper articles	1908-2004
ProQuest Historical Newspapers: Los Angeles Times	Historical news - newspaper articles	1881-1994
ProQuest Historical Newspapers: The New York Times	Historical news - newspaper articles	1851-2014
ProQuest Historical Newspapers: The Wall Street Journal	Historical news - newspaper articles	1889-2000
US Hispanic News stream	US Hispanic Newsstream provides full-text access from US publishers in Spanish and English to the most comprehensive selection of leading Hispanic newspapers, newswires, websites, and blogs.	NA
US Major Dailies	US Major Dailies provides complete and timely coverage of local, national, and world events from five respected national and regional newspapers.	1980-current

Source: https://search-proquest-om.ezproxy.fiu.edu/databases/advanced?accountid=10901

Table 1A3. DAC list of ODA recipients.

DAC List of ODA Recipients
Effective for reporting on 2014, 2015 and 2016 flows

Least Developed Countries	Other Low Income Countries (per capita GNI <= $1 045 in 2013)	Lower Middle Income Countries and Territories (per capita GNI $1 046-$4 125 in 2013)	Upper Middle Income Countries and Territories (per capita GNI $4 126-$12 745 in 2013)
Afghanistan	Democratic People's Republic of Korea	Armenia	Albania
Angola	Kenya	Bolivia	Algeria
Bangladesh	Tajikistan	Cabo Verde	Antigua and Barbuda[2]
Benin	Zimbabwe	Cameroon	Argentina
Bhutan		Congo	Azerbaijan
Burkina Faso		Côte d'Ivoire	Belarus
Burundi		Egypt	Belize
Cambodia		El Salvador	Bosnia and Herzegovina
Central African Republic		Georgia	Botswana
Chad		Ghana	Brazil
Comoros		Guatemala	Chile[2]
Democratic Republic of the Congo		Guyana	China (People's Republic of)
Djibouti		Honduras	Colombia
Equatorial Guinea[1]		India	Cook Islands
Eritrea		Indonesia	Costa Rica
Ethiopia		Kosovo	Cuba
Gambia		Kyrgyzstan	Dominica
Guinea		Micronesia	Dominican Republic
Guinea-Bissau		Moldova	Ecuador
Haiti		Mongolia	Fiji
Kiribati		Morocco	Former Yugoslav Republic of Macedonia
Lao People's Democratic Republic		Nicaragua	Gabon
Lesotho		Nigeria	Grenada
Liberia		Pakistan	Iran
Madagascar		Papua New Guinea	Iraq
Malawi		Paraguay	Jamaica
Mali		Philippines	Jordan
Mauritania		Samoa	Kazakhstan
Mozambique		Sri Lanka	Lebanon
Myanmar		Swaziland	Libya
Nepal		Syrian Arab Republic	Malaysia
Niger		Tokelau	Maldives
Rwanda		Ukraine	Marshall Islands
Sao Tome and Principe		Uzbekistan	Mauritius
Senegal		Viet Nam	Mexico
Sierra Leone		West Bank and Gaza Strip	Montenegro
Solomon Islands			Montserrat
Somalia			Namibia
South Sudan			Nauru
Sudan			Niue
Tanzania			Palau
Timor-Leste			Panama
Togo			Peru
Tuvalu			Saint Helena
Uganda			Saint Lucia
Vanuatu[1]			Saint Vincent and the Grenadines
Yemen			Serbia
Zambia			Seychelles
			South Africa
			Suriname
			Thailand
			Tonga
			Tunisia
			Turkey
			Turkmenistan
			Uruguay[2]
			Venezuela
			Wallis and Futuna

(1) The United Nations General Assembly resolution 68/L.20 adopted on 4 December 2013 decided that Equatorial Guinea will graduate from the least developed country category three and a half years after the adoption of the resolution and that Vanuatu will graduate four years after the adoption of the resolution.
(2) Antigua and Barbuda, Chile and Uruguay exceeded the high income country threshold in 2012 and 2013. In accordance with the DAC rules for revision of this List, all three will graduate from the List in 2017 if they remain high income countries until 2016.

Source: DAC, OECD.

Table 1A4. Category of disaster.

Category	Types of Disaster	Natural Disaster
Biological	Animal Accident Insect Infestation Epidemic	No
Climatological	Wildfire Drought	No
Extra-terrestrial	Impact	No
Geophysical	Mass movement (dry) Earthquake Volcanic activity	Yes
Hydrological	Flood Landslide	Yes
Meteorological	Storm Fog Extreme temperature	Yes
Technological	Transport accident Miscellaneous accident Industrial accident.	No

Source: CRED Database (http://emdat.be/emdat_db/)

Table 1A5: Description of key variables

Variable	Label	Description	Source
ODAcom	US ODA commitments (country/year)	US bilateral ODA commitments in 2010 US dollars.	DAC, OECD.
ODAdisb	US ODA disbursements (country/year)	US bilateral ODA disbursements in 2010 US dollars.	DAC, OECD.
AidHum	US humanitarian aid disbursement (country/year)	US bilateral humanitarian assistance in 2010 US dollars.	DAC, OECD.
foodaid	US food aid disbursement (country/year)	US bilateral food aid disbursements in 2010 US dollars.	DAC, OECD.
CitGen	General news citations (country/year)	Search query omitted words/texts relevant to any natural disaster and foreign aid.	ProQuest News and Newspaper.

Table 1A5: Description of key variables (cont.)

Variable	Label	Description	Source
CitDis	Disaster news citations (country/year)	Number of natural disaster citation.	ProQuest News and Newspaper.
CitOda	ODA news citations (country/year)	This variable only includes aid-related words.	ProQuest News and Newspaper.
disasterno	Natural disasters (country/year)	Recorded natural disasters in each US ODA recipient country.	Database of the Center for Disaster Epidemiology Research (CRED).
totaldeaths	Natural disaster fatalities (country/year)	Lives lost during natural disasters.	CRED database.
totalaffected	People affected (country/year/natural disaster)	People affected by natural disasters.	CRED database.
tdamage	Property and infrastructure damage from disasters (dollar/country/year)	Estimated damage caused by a natural disaster.	CRED database
PGDP	Per Capita GDP (country/year)	Per capita real GDP valued in 2010 dollars.	https://data.worldbank.org/

Population	Population(millions/Country/year)	Population (millions)	United Nations (UN) Population Division.
trade	US bilateral trade balance (country/year)	US bilateral balance of trade	US Census Bureau.
pctagreeus	US friend in UN general assembly voting.	UN General Assembly roll-call votes.	Eric Voeten, Harvard University's Data verse.
Polity/Freedom Recoded as -10 to -6=1=Autocracy, -5 to 5=2=Anocracy, 6 to 10=3=Democracy	Regime type	On a 21-point scale, the 'Polity Score' is measured between -10 (hereditary monarchy) and +10 (consolidated democracy).	Project Polity IV, Center for Systemic Peace (CSP).

Table 1A6. Monotonic transformation of variables

Variable Name	Lowest numerical value	Transformation
LODAcom	0	LODAcom=log(1+ODAcom)
LODAdisb	-593.64001	LODAdisb=log(594.64001+ODAdisb)
LAidHum	0	LAidHum=log(1+AidHum)
Lfoodaid	-95.64	gen Lfoodaid=log(95.64+1+ foodaid)
LCitGen	0	LCitGen=log(1+CitGen)
LCitDis	0	LCitDis=log(1+CitDis)
LCitOda	0	LCitOda=log(1+CitOda)
LPGDP	0	LPGDP=log(1+PGDP)
LPopulation	0	LPopulation=log(1+Population)
Ltrade	-343078.78	Ltrade=log(343079.78+trade)
Lpctagreeus	0	Lpctagreeus=log(1+pctagreeus)
Ldisasterno	0	Ldisasterno=log(1+disasterno)
Ltotaldeaths	0	Ltotaldeaths=log(1+totaldeaths)
Ltotalaffected	0	Ltotalaffected=log(1+totalaffected)
Ltdamage	0	Ltdamage=log(1+tdamage)
LPODAcom	0	LPODAcom=log(1+PODAcom)
LPODAdisb	0	LPODAcom=log(1+PODAdisb)
LPAidHum	0	LPAidHum=log(1+PAidHum)
LPfoodaid	-4.019513	LPfoodaid=log(5.019513+ Pfoodaid)
LPCitGen	0	LPCitDis=log(1+PCitDis)
LPCitDis	0	LPCitGen=log(1+PCitGen)
LPCitOda	0	LPCitDis=log(1+PCitDis)
LPCitOda	0	LPCitOda=log(1+PCitOda)
LPtrade	-4638.0938	LPtrade=log(Ptrade+4639.0938)

Note: L stands for natural log, which is $Log_e N$.

Chapter 2

Hurricane Maria and Housing Market in Puerto Rico

2.1 Introduction:

The US mainland and territorial areas have experienced sixteen natural and weather disasters since 2015, and the estimated damage is around 22 billion dollars[25]. The Atlantic and Gulf coasts are particularly vulnerable to powerful storms that cause extensive wind and water damage (Below et al., 2017). On September 20, 2017, a category four hurricane (Hurricane Maria) came ashore in Puerto Rico, the deadliest ever recorded[26]. A category five hurricane (Hurricane Irma) touched base on the Island two weeks prior. Many regions of Puerto Rico were waist-deep in floodwaters, and storm surges and flash floods stranded thousands of residents (Hinojosa & Meléndez, 2018). This devastating storm damaged[27] thousands of houses and left most people without power for days.

In this chapter, we analyzed the impact of Hurricane Maria on the housing market in Puerto Rico following its landfall in 2017. A house's physical and local characteristics determine the housing value in a non-hurricane setting. But exposure to a hurricane and hurricane-related factors would adversely affect the home value. This phenomenon can

[25] This average information is based on the https://coast.noaa.gov/states/fast-facts/hurricane-costs.html. Damages from weather and climate events in the United States from 1980 to 2020 is approximately 2 trillion dollars.

[26] This 174 mph hurricane was the deadliest since Hurricane San Felipe Segundo struck this tiny Caribbean Island in 1928.

[27] The FEMA categorization of non-repairable homes, flood-damaged homes, and roof damage shows the amount and concentration of storm damage (Hinojosa & Meléndez, 2018).

separate the net impact of the hurricane shock on the housing market using Rosen's(1974) hedonic property valuation method.

There are variants of hedonic price determination available in the literature. The general hurricane effect[28] (Bin & Polasky, 2004; Zivin et al., 2020) is widely studied in hedonic valuation literature. More specifically, the hurricane-led storm surge or inundation effect (Barr et al., 2021; Cohen et al., 2021) is another common hedonic model found in the literature. Furthermore, the combined impact of the storm surge and the flood zone (Bin & Polasky, 2004; Morgan, 2019; Muller & Hopkins, 2019; Ortega & Taṣpınar, 2018) is also frequently studied in the literature. At the same time, the other notable conventional hedonic model is the effect of flood risk premium on home values (Bin & Landry, 2013; Peklak, 2020; Pollack & Kaufmann, 2022).

In this research, we investigated the effect of Hurricane Maria on the values of homes in Puerto Rico sold after Hurricane Maria's landfall in 2017. We chose Puerto Rico for two reasons: the housing market in Puerto Rico behaves differently from the mainland US. The Island’s housing prices have experienced a slump since 2005 due to non-hurricane factors (Hinojosa & Meléndez, 2018). Hence, if we can segregate the net hurricane effect, apart from the economic factors contributing to the soaring housing price, it will significantly contribute to the literature. We can then ascertain that Hurricane Maria significantly reduced the Island's housing prices. Second, this is the first systematic study on the housing market in Puerto Rico to explain price determination from physical or local characteristics perspectives and the occurrence of natural disasters.

[28] The hurricane effect was investigated by various authors, for example, Aqeel (2011), Beracha & Prati (2008), Fang et al. (2021), Murphy & Strobl (2009) and Y. Zhang & Peacock (2009).

Our analysis uses Zillow's home sale, American Community Survey (ACS), and National Oceanic and Oceanographic Association's (NOOA) hurricane data. We collected the data between 2018 and 2021, and Our sample size consists of 1001 single-family homes. No pre-hurricane Maria housing data was available during our investigation. The primary goal is to determine whether Hurricane Maria's landfall in 2017 lowered housing prices. Furthermore, our secondary goal is to identify a buffer zone of price reduction for hurricane-affected homes.

We ran a primary hedonic function with various extensions to determine how Puerto Rico's housing price is determined. The primary hedonic function predicted that three and four-bedroom houses are in greater demand. The number of bathrooms, net living area, homeowner's association fee (HOA), and the number of parking significantly increased home values. We further found that homes up to the 12-mile buffer distance from Maria track lower the home values. Again, home price drops when located on the left side of the hurricane track.

We also found home value decline for the houses aged over 40 plus years and exposed to category one or two-level hurricane wind. Furthermore, due to the tremendous windspeed, the second-story and above homes were harmed more than the ground-floor homes, lowering their value over time. Finally, our findings revealed that already in a flood zone and within a certain buffer distance could reduce their price.

Our findings revealed that Hurricane Maria discounted home values. To confirm that there is a distinct price difference between impacted (treated) and non-affected houses (control), we employed Difference-in-Difference (DID) and Regression Discontinuity Design (RDD) estimation techniques. The treatment effect assessment captured the price wedge due to the hurricane exposure. According to our treatment impact estimates, the storm effect on home prices is most potent between 3-miles and 6-miles buffer. The treatment effect is substantial on the left side of the hurricane eye.

The rest of the article is structured as follows. The background on Puerto Rico and Hurricane Maria is provided in Section 2.2, followed by a literature review. In Section 2.3, we explained the data and econometric framework. In section 2.4, we present our empirical findings. Section 2.5 describes the discussion and policy implications. The paper concluded with Section 2.6, including a bibliography and an appendix.

2.2.1 Puerto Rico Economic Profiles and Hurricane Occurrences:

Puerto Rico is a Caribbean Island and a US autonomous region in the northeast Caribbean Sea. This US[29] Commonwealth territory is home to over three million people. Pharmaceuticals, electronics, textiles, petrochemicals, processed foods, clothing, and textiles[30] are among the mainstays of the local economy. The tourism industry[31] of this island is also well-known. The single-family housing unit accounts for 69 percent of the

[29] 2019 American Community Survey Profile, https://data.census.gov/cedsci/table?g=0400000US72&d=ACS%205-Year%20Estimates%20Data%20Profiles&tid=ACSDP5Y2019.DP05

[30] https://welcome.topuertorico.org/economy.shtml

[31] In 2019 tourism revenue was US $5.51 billion, https://www.statista.com/statistics/814818/puerto-rico-tourism-revenue/

housing[32] in Puerto Rico. Owner-occupied housing accounts for 68.1 percent of the 1,192,654 occupied housing units[33].

Puerto Rico is hurricane-prone, with four major hurricanes hitting the island in the last ten years. During the 2017 hurricane season, two major hurricanes struck the island. Hurricane Irma made landfall on the island on September 6, 2017. It was a category five hurricane with over 185 miles per hour with sustained winds. However, when it landed on the island, the gusting wind reached 74 mph near San Juan, the capital. According to the National Hurricane Center, although Irma did not directly hit Puerto Rico, 10 to 15 inches of rainfall fell on high elevations. Inundation levels 1 to 2 feet above ground level occurred along the island's coast. The damage was over $1 billion, with three people killed (Welton et al., 2020).

On September 20, 2017, category four hurricane Maria hit the island less than two weeks later. Hurricane Maria struck Puerto Rico with winds of 174 mph, making it the most powerful hurricane to strike the island since 1928. The US Geological Survey (USGS)[34] observed an average inundation of 3 to 9 feet across the island. Hurricane Maria dumps massive amounts of rain[35] on the island, and the death toll from the storm is

[32] 2019 American Community Survey Profile, https://data.census.gov/cedsci/table?g=0400000US72&d=ACS%205-Year%20Estimates%20Data%20Profiles&tid=ACSDP5Y2019.DP04&hidePreview=true

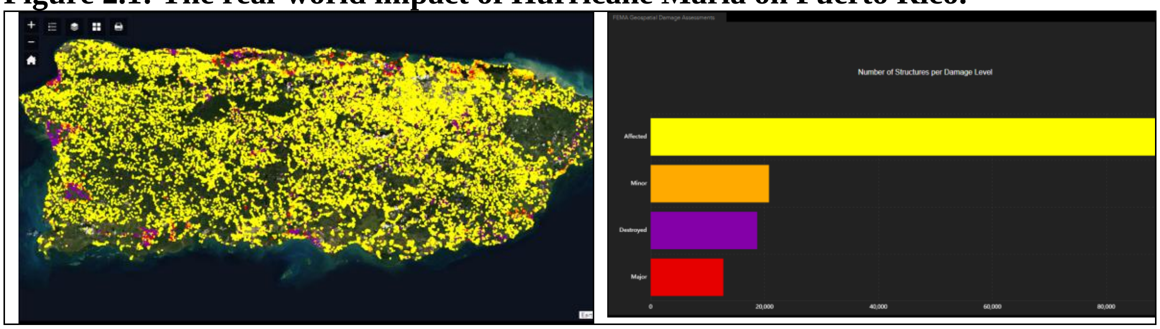
[33] American Community Survey Profile, www.census.gov

[34] Storm surge of 6-9 feet caused catastrophic flooding and island-wide flash flood alerts as Maria inundated Puerto Rico with 20–35 inches of rain (see https://recovery.fema.gov/funding-in-action/mariaPR7).

[35] According to NOAA report on one occasion nearly 38 inches rain was recorded during the landfall (see https://www.nhc.noaa.gov/data/tcr/AL152017_Maria.pdf).

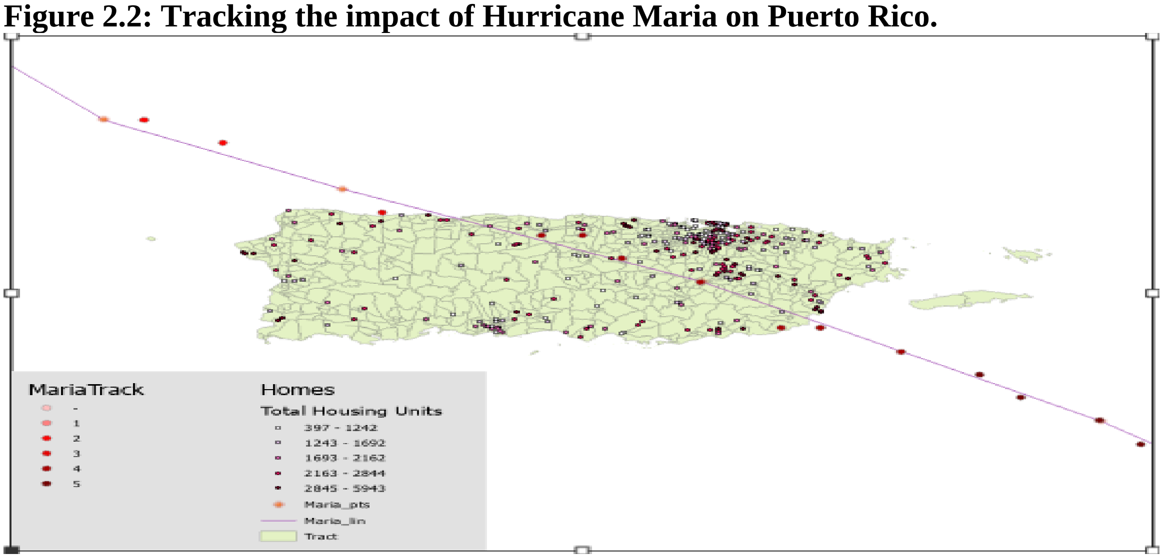
questionable. Several media outlets[36] predicted over 2000 deaths, compared to the government's initial estimate of 65. According to post-hurricane reports from the National Hurricane Center, Hurricane Maria was the third most expensive hurricane in US history, with an estimated damage of $100 billion[37]. Figure 2.1 depict the damage caused by Hurricane Maria below, and our sample frame, along with Hurricane Maria's path, is portrayed in figure 2.2.

Figure 2.1: The real-world impact of Hurricane Maria on Puerto Rico.



Source: ESRI website.

Figure 2.2: Tracking the impact of Hurricane Maria on Puerto Rico.



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[36] BBC (see https://www.bbc.com/news/world-us-canada-45338080), CNN (see https://www.cnn.com/2018/08/28/health/puerto-rico-gw-report-excess-deaths/index.html), NPR (see https://www.npr.org/2018/08/28/642615337/hurricane-maria-caused-2-975-deaths-in-puerto-rico-independent-study-estimates and Reuters (see https://www.reuters.com/article/us-usa-puertorico-maria/puerto-ricos-death-toll-from-hurricane-maria-raised-to-nearly-3000-idUSKCN1LD2DK).

[37] https://www.wunderground.com/cat6/hurricane-maria-damages-102-billion-surpassed-only-katrina

2.2.2 Literature Review:

Neighborhood and location variables affect housing prices, but housing characteristics are the most critical factors. The traditional econometric framework becomes a Hedonic pricing model when environmental and natural disaster-related features are considered for housing price determination. A conventional hedonic model can capture partial valuation on a smaller scale. Because exogenous natural shocks, such as hurricanes, can shake a community and disrupt the real estate prices in the impacted areas. Therefore, considering pertinent factors would provide a better glimpse of a home valuation in any locality.

There are convincing findings in the literature showing that disaster-driven housing price increases are short-term effects. According to Murphy and Strobl (2009), the price rise is just transitory owing to a short-term supply shortfall. It will, however, be altered in the medium and long term as supply progressively recovers to pre-crisis levels. Using metropolitan[38] data from US coastal towns in the North Atlantic Basin, they found that a regular hurricane positively affects property values for several years. Three years after the event, the effect is no longer as strong, but it is still between 3 and 4 percent.

The Atlantic and Caribbean oceans surround the island of Puerto Rico. As a result, flooding is a common occurrence. Flood damage varies depending on the distance from the coast to the mainland, implying that property prices in those areas also vary. Using a

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[38] The author uses the Census Bureau's Housing Patterns and Core-Based Statistical Areas (CBSA). Their housing data is a quarterly housing index data. CBSAs stands for the Office of Federal Housing Enterprise Oversight (OFHEO).

hedonic property price method[39], Bin & Kruse (2006) investigated the consequences of flood hazards[40] on residential property values on the mainland and outer banks. The critical identification in their study was comparing the housing price between 500-year-old and 100-year-old floodplains. Their results suggested that property values in non-flood-affected zones are 5-10% lower. On the other hand, being in a flood zone prone to inundation raises property prices.

According to Graham Jr & Hall Jr (2001), declining residential property values in hurricane-prone[41] areas may be considered high-risk endeavors for potential home buyers. As a result, they investigated the link between storm[42] home values in South Carolina. Throughout the study, the region's home values have risen steadily. Hurricane frequency had increased in the study area, hurting housing prices. There had been no significant price change due to Hurricane Fran; homebuyers and sellers regarded its arrival as random. Negative indications and implications of the storm variables indicated a connection between the emergence of Hurricanes Floyd and Bonnie and consequent property prices.

[39] According to Bin & Kruse (2006), the human/flood hazard interaction is worth studying because coastal property values have risen by an average of 7% annually for the past five decades.

[40]Their work was motivated by the fact that long-term sea level rise may increase inundation for low-lying communities, storm damage, flood, and beach erosion. NFIP flood maps were used to measure flood zone housing prices.

[41] Market participants' perceptions of storm landfalls may change which might lead to lower housing values.

[42]Four storms, Bertha, Fran, Bonnie, and Floyd were studied for their frequency by the authors. Hurricanes Bertha, Fran, Bonnie, and Floyd all made landfall in the region in 1996, 1998, and 1999, respectively.

Storm damage[43] followed by flooding could lower property values in coastal areas, which are vulnerable to significant risks and financial burdens due to their high vulnerability to hurricane damage[44] (S. K. Kim & Peiser, 2020). As a result, the primary goal of Kim and Peiser (2020) was to see a major storm's impact on housing prices in floodplains, risk perceptions, and the interaction between storm frequency and flood exposures. We analyzed the effects of hurricane exposure on homes struck by storms, a house that had not, and those on the left side of the hurricane track. Furthermore, we did not examine the impact of hurricane-caused flooding on housing prices; instead, we wanted to see whether being in a flood zone affects the price of homes in Puerto Rico.

Natural disasters temporarily affect housing prices that fade after a while. According to Below et al. (2017), one of the reasons for lower housing prices in Puerto Rico is a demand-supply mismatch. Residents of Puerto Rico were impacted by Hurricane Maria, causing them to fall behind on their mortgage payments and increase their chances of foreclosure. The 2006–2016 economic crisis and Hurricane Maria devalued Puerto Rico's housing market, causing many families to leave, remain in broken residences, or relocate to another family (Hinojosa & Meléndez, 2018[45]).

[43]Recent research in Florida's Lee County Information concerning the possibility of future storms reduces property prices by at least 19 percent, according to Hallstrom and Smith (2005).

[44] Storm-driven flood danger reduces Miami-Dade County home prices (S. K. Kim & Peiser, 2020).

[45] Due to a discrepancy in housing supply and a drop in housing demand, they argued, Puerto Rico's median house prices have dropped at least 10% since 2005. Between 2016 and 2018 at least 50% of island counties had their median property values fall, while the other 50% saw a little rise.

According to Glaeser et al. (2005), changes in housing service regulations were among the most significant changes in the American housing market. Nonetheless, this change has received insufficient research and debate. A drop in cement sales[46] and building permits[47] are two other causes of housing price decline on the Island and the demand-supply imbalance (Hinojosa & Meléndez, 2018).

In the hedonic model literature, comparing before and after hurricanes is a standard norm for capturing the hurricane effect. For example, Bin and Polasky (2004) calculated[48] the impact of a flood on house values in Pitt County, North Carolina, before and during Hurricane Floyd, which produced significant flooding. According to their research, homes in floodplains are worth less than comparable homes outside of floodplains, and this discount was evident[49] after Hurricane Floyd. They claimed that the massive devastation caused by Hurricane Floyd changed property owners' perceptions of flood risks and the value of properties in floodplains.

Neighborhood characteristics influence a potential buyer's decision to purchase a home in specific geolocation and the housing market. Díaz-Garayúa (2009) examined their hedonic price determination by discussing the importance and outcomes of neighborhood

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[46] The author found that the 68 percent decline in the cement sale in Puerto Rico between 2009 to 2018 discounted the price of houses.

[47] Hinojosa & Meléndez (2018) also said the decline in construction permit issuing raised demand for single-family houses, followed by three to four units and five or more units.

[48] Authors used structural, neighborhood, and environmental attributes to measure the hedonic function in North Carolina.

[49] In a floodplain, property values drop by an estimated 5.7 percent.

effects on home prices inside the San Juan MSA, Puerto Rico, and the impact of ethnic groups'[50] presence. He hypothesized that these additional criteria aid in forming a housing submarket with comparable demographics and price ranges; specifically, housing submarkets are interdependent[51]. In the San Juan MSA area, purchasing a house in a Dominican diaspora area negatively correlated with median housing values.

The population density of Puerto Rico is the third highest[52] of any US State or territory. Aside from standard price determination, the disparity between housing needs for the young population of Puerto Rico may cause prices to rise. Garcia Zambrana (2009) looked into this possibility and discovered that Esperanza was overcrowded, with four generations of a family living in the same house. The author showed that those between 35 and 54 who earned less than $40,000 lived in overcrowded dwellings. The majority of overcrowding cases (70%) involved young couples or single mothers aged 16 to 40 who lived with their parents. This aspect of the Puerto Rican housing market involves land constraints when building a new home. The key finding was that families in Puerto Rico required additional bedrooms to accommodate their extended family.

The influence of different natural hazards on the housing market altered the traditional hedonic pricing model. The hurricane-driven impact dominates the literature, so Ewing et al. (2007) investigated the single-family housing market's short and long-term response to a wind disaster. According to the authors, hurricanes had a short-term impact

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[50] Based on the literature (Kiel & Zabel, 1996; King & Mieszkowski, 1973; Macpherson & Sirmans, 2001) the author cited , living in relatively segregated neighborhoods costs more than similar housing elsewhere.

[51] Interdependent in the sense that people prefer neighborhood with their dominant diaspora.

[52] https://www.statista.com/statistics/183588/population-density-in-the-federal-states-of-the-us/

and immediate detrimental influence on local residential housing market price fluctuations. On the other hand, the tornado effect may have a long-term effect. The reason for this is that no single hurricane has a lasting impact. The overall effect could be significant, contributing to a longer-term price drop. The same argument applies to a tornado; their findings indicated that house values fall soon after a tornado or hurricane, but only for a brief period.

The DID effect helps determine the hurricane treatment impact by comparing before and after housing market changes. After Hurricane Sandy, Cohen et al. (2021) calculated the influence of hurricane shocks on single-family property prices in NYC. Their research looks at differences in single-family home values not directly impacted by storm surges[53]. The positive vs. negative[54] shock following the storm surge was the basis of their analysis. The authors achieved this by manipulating the FEMA borderline and subtracting the storm wave and wave distances. Using difference-in-difference estimation, they find that general shocks do not affect house prices. Housing costs increased by 6–7% when located a mile away from a negative shock, while the corresponding positive shock had no effect.

Similarly, Ortega and Taspinar (2018) investigated whether the housing demand in New York City has shifted towards more minor flood-prone areas since Hurricane Sandy made landfall. There are six Hurricane Evacuation Zones (HEZs) in the city. They permit

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[53] Cohen et al. (2021) examined distance from the surge on buffer (price or treatment) effects for non-flooded residences between 0.03 to 1 mile from the surge.

[54] Negative shocks groups are home close to the surge than FEMA flood limits and positive shocks are homes away from FEMA boundary (Cohen et al., 2021).

"treatments" of 0 (no damage), 1 (light damage), and 2 (significant damage). Then, they compare post-Sandy prices between the treatment and control groups. In their difference-in-differences model, the treatment group seemed to have a long-term impact, with a 17 to 22 percent decline in home values. In addition, the treatment effect factors suggested that mean home values would increase more than anticipated for properties closer to Sandy[55]. The price per square foot would have fallen by 6% to 7% in areas where the storm surge was a mile nearer than anticipated (from FEMA inundation zones).

According to another study by Yi & Choi (2020), the 2008 Iowa Des Moines flood-affected housing prices. The authors calculated the housing market price function using home transaction data from 2000 to 2012. This study utilized the DID and Difference in Difference in Differences (DDD) techniques to assess the flood's impact. Housing divisions in 100- and 500-year floodplains were the primary treatment category, whereas the control group was homes located outside of both floodplains[56]. In addition, the author controlled inundated areas with pre-inundation geographical effects to capture the flood effect on housing prices through the post-flood inundation effect[57]. The contribution of this study was to show that homes in an unexpected flooding zone experienced lower home prices in

[55] The authors divided flood locations into four categories: dry FEMA floodplain, FEMA floodplain impacted by storm surge, surge outside FEMA floodplain, and neither floodplain nor storm surge.

[56]The treatment group was defined as the area that had been affected by flooding, whereas the control group was defined as the region that had not been affected by flooding.

[57] To figure out how the Des Moines area changed after the 2008 flood, authors split the city into six parts: 100- and 500-year floodplains submerged, 100- and 500-year floodplain not flooded, non-floodplain inundation and non-flooding of non-floodplain area.

the future. However, prospective homebuyers still purchased homes situated in 100-year floodplains.

In 1992, Hurricane Andrew wreaked havoc on Florida, causing long-term damage to the housing market. In this regard, knowledge of a previous hurricane could impact the house's future value. Hallstrom & Smith (2005) investigated The responses of housing values to new storm information[58] . The assumption was whether the home was in or out of the Special Flood Hazard Area (SFHA) and the storm zone. The authors' isolated the effects of the information conveyed by the storm by calculating an interaction between the two conditions. Their DID framework for housing prices showed that in Lee County, Florida, Andrew reduced SFHA dwellings price by 19%.

Following a hurricane, the pricing dynamics in the impacted areas may not reflect pre-existing demand-supply-side characteristics of the housing market. Zivin et al.(2020) used microdata from Florida between 2000-2016 to investigate post-hurricane equilibrium dynamics[59] in local housing markets. The research used buffers, hurricane exposure, a place that has ever been within a 64-knot wind velocity range near a hurricane's track, and contact with an intense 96-knot wind speed. The authors divided the exposure variable into 65-95 knots and over 96 knots[60] to represent the uncertainty of the hurricane's impact on

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[58] Hallstrom & Smith (2005) evaluated if hazardous property values changed to the availability of storm's information.

[59] The central idea of their investigation was based on how population dynamic affected the housing market following a hurricane.

[60] This exposure identification required proximity to the hurricane path and experienced constant high wind speed (Zivin et al., 2020). Eventually, they compared the damaged house due to wind or precipitation with the overall general equilibrium of housing market.

the housing market. Their findings showed that house prices rose three years after the storm, despite decreased sales[61] (transactions) and that the hurricane had little long-term influence on housing demand in the impacted areas.

One concern we had with the hedonic value analysis was that the number of bedroom variable coefficients was negative. It may be due to the multicollinearity of the number of bedroom with the number of bathroom variables. We used dummy variables to control it, ranging from a single bed to a maximum of one and two-bedroom houses. We believe that population density, apart from bathroom collinearity, could contribute to this occurrence. Glaeser et al. (2005) discovered that higher population density acted as a negative externality[62] on home demand, eventually lowering housing values. When looking at the population density of Puerto Rico, it becomes clear that the northwest side is densely populated and may have a hidden demand for houses with more bedrooms. As a result, despite the higher demand for large bedrooms, the home price in northwest Puerto Rico is lower than in other parts of Puerto Rico. This negative correlation between bed and value may influence the negative bed coefficient.

Dresden-based researchers Pommeranz and Steininger (2020) investigated the effects of the categorization of flood-prone areas (the lowest, medium, high, and the highest) on the price of residential real estate. They discovered negative indirect impacts

[61] A portion of the housing supply is destroyed by storms and then rebuilt.

[62] This is a theoretical paper which measure the utility of a potential buyer. As a result, increased population density has a negative influence on future inhabitants' utility since prospective house purchasers are ready to pay more for a low-density community with more amenities.

from the surrounding attributes but no statistically significant direct effects[63]. The authors' findings demonstrated that the significance of the unintended consequences of the flood was equal to -6.5% for homes and -4.8% for condominiums.

Komarek & Filer (2020) used a difference-in-differences model to predict how major flooding events[64] affected the real estate market. Their research examined 137,348 residential property sales in southeast Virginia between 2007 and 2016. According to the findings, homes in high-risk flood zones stay 5–8 days longer[65] on the market. Their results revealed that the local suburban real estate market had stabilized following a severe weather event (Komarek & Filer, 2020).

Again, Saginor & Ge (2017) identified five major overlapping themes in the peer-reviewed literature on natural disaster housing price dynamics. The authors highlighted some themes in their research: waterfront views, closeness to beaches, storm impacts on home market and recuperation, storm effect mitigation by enhanced and tighter construction rules, and higher insurance premiums. Their study used a DID hedonic price model to determine the effects of multiple hurricanes on housing values in Brunswick County, North Carolina, between 1984 and 2007. They observed that in 1996, the three hurricane-affected counties had a powerful and adverse influence on house prices. In non-

[63] The direct and indirect impacts are influenced by properties in a neighborhood's flood zone, whereas the latter is calculated by considering a weighted average (Pommeranz & Steininger, 2020).

[64] Flooding event is generated by comparing 100- and 500-year floodplain. The 'Flood Zone' variable indicates a property's flood vulnerability. It's calculated using the Flood Zone indicator and a storm's duration.

[65] Staying longer in the market is related to the liquidity of the homes being sold.

hurricane years, economic variables were more likely to impact sales values than hurricanes and associated disasters.

Housing property adjacent to the Atlantic Ocean and Gulf shore is vulnerable to hurricanes. As a result, wind and flooding damage[66] to property was a real possibility during these storms (Below et al., 2017). From 1999 to 2012, the authors focused on property[67] sales in Dare County, North Carolina, a coastal region with many residential homes along the Atlantic Ocean. They found a 3.89 percent price decline 60 days after a hurricane in Dare County. This rebate, however, is only provisional and disappeared after 60 days following the storm[68].

There is evidence in the literature that high-rise buildings are more vulnerable to hurricanes than their low-rise counterparts. Kong & Liu (2022) found during their investigation[69] of the real estate market in Shenzhen, China, that the high-rise house price fell by 0.8 to 1.2 percent compared to the low-rise between 2013 and 2020 typhoon-affected houses. Typhoons would cost a 100-square-meter house 42,000 RMB (approximately $6,480). We took their identification and incorporated it into our hedonic model estimation.

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[66] To check the severity of storm damage, Below et al. (2017) shortlisted the storms by (1) damages over $25 million; (2) wind velocities over 100 mph within North Carolina coast; and (3) Dare County experienced tropical storm intensity wind or more.

[67] In their model specification, the authors have narrowed their focus to the Oceanfront, sound front, and inland properties.

[68] The authors labeled the post-hurricane period as 'Following (1–60 days)' and 'AFTER (61–90 days)'.

[69] The estimations based on difference-in-difference specification.

A potential buyer's first encounter with a hurricane is sometimes a random event because it helps them form an opinion about the hurricane's impact on future home values. However, with the experience of multiple hurricane exposure, they may be able to develop an adaptive expectation about future housing prices. Graham & Hall (2001) believed that the early hurricane experience in North Carolina would not significantly impact the local housing market. The subsequent hurricane experience, on the other hand, may have negative consequences. According to their estimates, the early hurricanes' exposure was a random experience for the locals. Therefore between 1996 and 1999, hurricanes Bonnie and Floyd had a damaging and considerable impact on home values in the coastal area of Northeastern North Carolina.

Hungary is susceptible to flooding, as its rivers originate in neighboring nations, so its residents know how flooding affects home values. Using the hedonic method at the ZIP[70] code level, Békés et al. (2016) found that flood risk[71] significantly reduced housing prices, particularly near major rivers. In addition, housing prices tend to be 1 percent lower in ZIP codes with greater inundation depths and along major rivers. Our research classified Hurricane Maria's storm surge inundation data and examined their effect on Puerto Rico's real easter sector.

In 1994, the city of Albany, Georgia, experienced the flood of the century because of tropical storm Alberto. Based on this occurrence, Atreya & Ferreira (2015) analyzed the link between flood risk information and fluctuations in the flood risk premium to determine

[70] Many different factors are considered when the ZIP code level flood risk hedonic price model estimation.

[71] Average inundation depth values measure flood risk

whether inundated properties were discounted compared to floodplain and non-inundated properties. They discovered that the price reduction for flooded properties was significantly higher than comparable non-flooded properties in the floodplain. Our research objective is markedly distinct. We are interested in their DID identification method. The authors split their sample group into four separate zones: flooding in the floodplain, inundated beyond the floodplain, and non-inundated in both categories. We want to create a similar buffer for Puerto Rico to distinguish whether the hurricane Maria-triggered flooding lower housing prices.

Depending on where a hurricane makes landfall, the short- and medium-term effects on home prices and sales volume in the United States may vary. These findings prompted Beracha & Prati (2008) to explore the impact of a major hurricane on residential real estate prices and volume in coastal U.S. states. Using housing transaction data by ZIP code in 2004-2005, they calculated the macroeconomic hedonic function of a real estate market. The authors found that house values and sale volume in afflicted ZIP codes temporarily fell in the two quarters following a hurricane. However, the market price returned to its pre-hurricane level after one year. The Zillow website did not track pre-Maria housing prices, so our analysis is limited to post-hurricane years.

Without environmental shocks, the housing market value depends on differences in amenity and location. Therefore, prices must converge globally. Harrison et al. (2001) conducted a DID study with houses located within 100-year flood plains (in Alachua County[72], Florida) for the establishment of a Special Flood Hazard Area (SFHA) by FEMA to determine the conditions under which it can deviate. According to the estimated results,

[72] The data came from the Florida Department of Revenue's real estate tax information.

homes within an SFHA zone sold for less than those outside the zone. Homes inside the SFHA exposed to environmental disasters experienced less than $1,000 loss in home value than those outside the SFHA.

On Jan. 7, 2020, a 6.8 earthquake hit Puerto Rico. The island was still recovering from the repercussion of Hurricane Maria. Hence, some homeowners may worry about their home's worth following the earthquake and storm. We are especially concerned about whether the earthquake impacted hurricane-affected homes. This double shock of natural disasters would have a different effect on the market price than a single disaster impact. Naoi et al. (2009) utilized the development of an earthquake on property values using a DID method with panel data. They noticed changes in people's earthquake risk perceptions after the quake. Those who migrate to a quake-prone area after a disaster and purchase a property will save far more money. We are interested in the volatility of the housing market in Puerto Rico caused by the earthquake and hurricane.

Most research focuses on the impact of hurricanes on housing and whether storms alone or in conjunction with flooding reduce housing prices. Sheldon & Zhan (2019) intuitively covered all the bases from the homeownership perspective. They combine disaster types into five categories of natural disasters: coastal, flood and rain, wind, and winter. Therefore, severe coastal disasters had an immense impact, decreasing homeownership by more than 30 percent, whereas severe flood and rain events reduced homeownership by nearly four percent (Sheldon & Zhan, 2019). They obtained inconclusive results regarding the effect of extreme wind events or winter disasters on homeownership decisions.

A cross-sectional study by Apergis (2020) focused on the localized effects of natural disasters. Because a cross-country approach to separating the relationship between home prices and natural catastrophes would show a worldwide trend (Apergis, 2020). The author used panel data of 117 nations from 2000 to 2018 to quantify the impact of natural calamities on housing values. Our data do not support a panel study. Nonetheless, his study showed that geological catastrophes have the biggest (negative) influence on housing values, especially considering the differential between minor and major disasters.

2.3 Methodology:

2.3.1 Econometric Model Specification:

The log-linear version of the Hedonic price model predominates the literature (Bin & Kruse, 2006; Graham Jr & Hall Jr, 2001). In our analysis, we employ the model's semi-log version. However, we must ensure that the value of Puerto Rico housing conforms to a normal distribution. We created a histogram and Kernel distribution to determine the normal distribution of housing values. Figure A2.1 in the appendices further explains the shape of the distribution. The histogram of the level form of the home sale price is skewed in both (normal and Kernel) density, whereas the log sale price of the home conformed to a normal distribution.

The location, timing of transactions over the research period, and certain economic circumstances influence home prices. A before-after comparison is standard in hurricane-induced hedonic model literature. Graham Jr. and Hall Jr. (2001) similarly examine home sales data while controlling for these general economic factors. Our primary objective of evaluating the post-hurricane Maria home price in Puerto Rico is consistent with the existing literature. We intend to test the following hypotheses for determining Puerto Rican housing prices concerning natural hazards and disasters.

Hypothesis A:

H_0: The housing prices within X miles of the hurricane track/eye follow the same pattern as the housing prices outside of X miles. The following DID log-linear hedonic model was applied to test the first hypothesis,

$$\boldsymbol{LSP_{ijt} = \alpha + \beta X_{ijt} + \gamma Z_{ij} + \delta HcnHit_{ij} + \sigma S_{m_{ijt}} + \theta S_{m_{ijt}} * HcnHit_{ij} + L_j + T_t + \varphi_{ijt}} \qquad (\mathbf{1})$$

Where, $\boldsymbol{LSP_{ijt}}$ is the vector of the log sale value of house *i* in neighborhood *j* during time *t*; and the variable $\boldsymbol{X_{ijt}}$ denotes the vector of home characteristics (square feet, bedroom bathroom, etc.). The variable $\boldsymbol{Z_{ij}}$ presents vector of location distance, such as distances from amenities, beaches, etc. $\boldsymbol{HcnHit_{ij}}$**,** is a dummy variable, takes a value of one when a house sold after one year of Hurricane Maria landfall, and zero otherwise. $\boldsymbol{S_{m_{ijt}}}$ is the dummy variable with a value of one if located within M miles of the hurricane track and zero otherwise. For the value of M, we consider different distance levels of 0-3, 0-6, 0-9, and 0-12 miles[73]. The interaction between $\boldsymbol{HcnHit_{ij}}$ and $\boldsymbol{S_{m_{ijt}}}$ captures the possibility of hurricane-led damage to the housing values. Additionally, we control time ($\boldsymbol{T_t}$) and location ($\boldsymbol{L_j}$) fixed effects. The $\boldsymbol{\varphi_{ijt}}$ denotes the disturbance error term.

[73] Literature indicated similar approach in Bin & Kruse (2006).

<u>Hypothesis B:</u>

H₀: No significant price difference exists between homes in the flood zone and those affected by the unexpected hurricane. For the second hypothesis, we employed the DID log-linear hedonic price model shown below,

$$\boldsymbol{LSP_{ijt} = \alpha + \beta X_{ijt} + \gamma Z_{ij} + \delta HcnHit_{ij} + \sigma I_{d_{ij}} + \theta H_{q_{ij}} * HcnHit_{ij} + L_j + T_t + \varphi_{ijt}} \qquad (2)$$

Here, $\boldsymbol{I_{d_{ij}}}$ represents dummy of whether the house faced any hurricane-led inundation; value one means it was in a flood zone and zero otherwise. The interaction between $\boldsymbol{HcnHit_{ij}}$ and $\boldsymbol{I_{d_{ij}}}$ captures the effect of hurricane distance buffer and flood zone exposure on the housing values.

<u>Hypothesis C:</u>

H₀: There is no significant price difference between houses in the hurricane track buffer zone and those on the left side of the hurricane track. For the third hypothesis, we employed the DID log-linear hedonic price model shown below,

$$\boldsymbol{LSP_{ijt} = \alpha + \beta X_{ijt} + \gamma Z_{ij} + \delta HcnHit_{ij} + \sigma I_{d_{ij}} + \theta H_{q_{ij}} * HcnHit_{ij} + L_j + T_t + \varphi_{ijt}} \qquad (3)$$

Here, $\boldsymbol{I_{d_{ij}}}$ represents dummy of whether the house is on the left side; value one means it was on the left side and zero otherwise. The interaction between $\boldsymbol{HcnHit_{ij}}$ and $\boldsymbol{I_{d_{ij}}}$ captures the effect of hurricane distance buffer and left side exposure on the housing values.

Hypothesis D:

H_0: There is no significant price difference between homes in the hurricane track buffer zone and those on the highest floor of the hurricane track.

Hypothesis E:

H_0: No significant price difference exists between houses in the hurricane track buffer zone and homes on the ground floor of a flood zone.

Hypothesis F:

H_0: There is no significant difference between the prices of homes in the hurricane track buffer zone and houses with different wind exposure or in the hurricane track's flood zone.

2.3.2 Data Collection:

We obtained our housing data from the Zillow[74] website. The Zillow Group[75] is the market leader among listed[76] real estate providers in the United States[77]. With 36 million monthly visits, the Zillow website is the most popular real estate website in the United States. According to Zillow's website, Zillow Offers buys and sells homes directly in dozens of markets across the country, allowing sellers to control the timeline.

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[74] https://www.zillow.com/

[75] "Zillow Group's brands, affiliates and subsidiaries include Zillow, Zillow Offers, Zillow Premier Agent, Zillow Home Loans, Zillow Closing Services, Zillow Homes, Inc. Trulia Out East StreetEasy and HotPads", as per the Zillow website.

[76] Notable sellers are Zillow, Trulia, Realator.com, Apartments.com, Homes.com, ForSaleByOwner.com, Redfin, Realtytrack, and NeighnorhoodScout.

[77] See https://www.statista.com/statistics/381468/most-popular-real-estate-websites-by-monthly-visits-usa/ for more details.

Our location of interest is the housing market in Puerto Rico. Since Hurricane Irma and Maria made landfall in 2017, we have meticulously sorted the sold properties from the Zillow website for data collection purposes. The Zillow website displayed 2,520 sold properties in Puerto Rico. Reviewing the timeline of sold properties, we discovered that Zillow's website provides data records from 2018 to 2021, which meets our needs precisely. Then, we gathered the link for every 2,520 properties to scrape the data.

We initially scraped data using version 8 of the freely available scraping platform Octoparse[78]. We carefully created a workflow of variables such as number of bedrooms, number of bathrooms, sold value, heating, cooling, electricity, water, sewer, roof, foundation, construction, parking, community amenities, parcel numbers, and year built. The initial test ran smoothly, but upon closer inspection, we discovered that the data lacked numerous vital pieces of information. In some instances, the data was present but incorrectly distributed among column headers. As a result, reshaping the data with this uneven distribution presented challenges because we did not know if they were authenticated data from the same web link. We attempted to match the data by manually examining each web link. This manual verification proved time-consuming, so we collected the data by writing a Python code scraper.

The python scraper contained the necessary variable for data scraping. Nevertheless, we encountered difficulties during the scraper code's trial run. The scraper stopped downloading after retrieving a few observations. The Zillow website blocks our IP address whenever it detects automated data downloads. We decided to use anonymous proxy IP addresses based on a recommendation from Python web scraping sources. A

[78] https://www.octoparse.com/

rotating proxy is ideal for scraping data automatically from specific websites. To circumvent the IP block by the Zillow website, we took the aid of Webshare[79], a provider of rotating proxy services. The rotating proxy strategy facilitated the collection of scraped data. The extraction process lasted for 76 hours[80].

2.3.3 Data Cleaning:

The Zillow website listed 2,520 homes sold between 2018 and 2021. Our primary variable of interest was the square footage of the homes, followed by the number of bedrooms, bathrooms, and other features. We used these three key variables as the benchmark for cleaning the collected data. A close examination of the scraped data revealed that many homes lacked the dimensions, number of bedrooms, and number of bathrooms. We consulted a different real estate website called Compass[81] to verify the data's integrity.

We cross-check the same house information on compass.com using the Multiple Listing Service (MLS) number associated with each property on Zillow. If we discovered the missing data on compass.com, we would replace it with our primary dataset for missing housing data. The Zillow website revealed another pattern for the house with missing data. Sometimes the home was listed as a single unit, and the number of bedrooms and bathrooms for multiple units was hidden in the overview section.

[79] https://www.webshare.io/ is a California based proxy web service provider. Their service offers different packages, such as buying custom proxy IPS as low as $0.043 per proxy IP address.

[80] Scraping started at 2.30 pm on October 14, 2021, and ended at 7 pm on October 17, 2021.

[81] www.compass.com

So for those homes, the list was generated by averaging[82] each property's number of bedrooms and bathrooms. A notable omission in our cleaned data is that some listings are development-ready land with no general structure. We also removed observations initially listed on Zillow but were deleted later. The final exclusion criterion in our data cleaning process is that we discovered duplicate listings. We meticulously sorted them and removed any duplicates.

The final dataset contains 1858 houses with the specified dimensions, number of bedrooms, and bathrooms. Then, based on the available literature, we compiled a sample of 1018 single-family homes. Thus, our unit of analysis in Puerto Rico is single-family homes. Finally, we matched the collected data on single-family homes with the 2010 American Community Survey (ACS) data, reducing our sample size to 1001 homes. The entire paper is based on 1001 single-family homes. Table 2.1 lists the variables which finalized after our cleaning.

Table 2.1. House characteristics

Variable	**Description**	**Type**
Value	Value of each home in a current year US dollar	Continuous
Bed	Number of bedrooms per house	Continuous
Bath	Number of bathrooms per house	Continuous
SQFT	Size of each house in square feet	Continuous
Soldon	Date of sale	Continuous
AgeHouse	Denote the age of each house	Continuous
HOAfee	Yearly homeowners' association (HOA) fee in US dollars	Continuous
HOADum	HOA dummy. 1= has an HOA fee 0=No HOA fee	Categorical

[82] For example, one unit has 2 bed and 2 bath, while another has 3 bed and 2 bath in the types of units available. Then we replace the missing number of bed and bath of as 3 bed and 2 bath. This problem is acute in condominium type listed sales.

Lotsize	Size of available land attributed to the property in square feet.	Continuous
Level	Location of the floor where the house is located.	Continuous.
ConstructionMat	Material needed to construct each house.	Categorical
FoundationMat	Material needed to build the foundation of each house.	Categorical
RoofMat	Material needed to build the roof of each house.	Categorical
FloorMat	Material needed to build the floor of each house.	Categorical
Sewer	Whether the house has a sewerage connection, Options are public or private.	Categorical
Water	Whether the house has a water connection, Options are public and private.	Categorical
Heating	A house equipped with a heating option.	Categorical
Cooling	A house equipped with a cooling option.	Categorical
Fullbath	The number of full bathrooms in each house.	Continuous
Hometype	Types of houses	Categorical
Ownership	Type of ownership	Categorical
Attic	Features of attic	Categorical
Parking space	The number of parking spots.	Continuous

Source: Scraped from Zillow website

Notably, the value of each home in our sample is expressed in current US dollars between 2018 and 2021. Although some authors in the literature (Bin & Kruse, 2006; Graham Jr & Hall Jr, 2001) analyzed price determination based on constant US dollars to control inflation. We did not employ a similar strategy. We also added a dummy variable for Puerto Rico's 78 counties to control location-fixed effects and four dummy variables for 2018 to 2021 to capture the heterogeneity resulting from time-fixed effects[83].

[83] Controlling location and year fixed effects by a dummy variable is a standard practice in literature (Bin & Kruse, 2006)

In addition to these core variables of interest in Table 2.1, we extracted detailed information about each house to control the impact of additional home characteristics on housing prices. We pulled this variable in comma-separated text format based on the exterior features of each home that we believe significantly impact the price. We separate them into six columns using the text-to-column option in Microsoft Excel. We discovered the following list of features regardless of the Excel column: balcony, concrete, dog run, fencing, French doors, lighting, irrigation system, outdoor kitchen, outdoor grill, outdoor shower, patio, rain barrels/cisterns, sidewalk, rain gutters, sliding doors, storage, sauna, stucco, tennis court, hurricane shutters, and wood.

We utilized Microsoft Excel's filter mode to determine each feature's frequency and create a column with the highest number of occurrences across all property addresses. In addition, we selected the balcony, whether the property is fenced, equipped with hurricane shutters, a sliding door, and a sidewalk based on the most popular criteria.

We extracted utility information directly from the Zillow website, separately listed in the housing details tab. The Zillow website contains detailed information about water access and sewer connections but limited information about electricity connections. Therefore, we scraped the sub-information tabs titled "utility property" with various details about a home's utilities. Using the Excel text tool, we organize the variables into columns. These utilities included BB/HS internet availability, cable availability, electricity availability, fiber optics, fire hydrant, natural gas connection, phone availability, propane, and sewer availability/connection.

We cross-checked sewerage and water information extracted directly from this sub-column of the electric utility's database, and if a gap existed, we filled it. Using data filtered across columns, we compiled most data on electricity connections. Then, after screening all other subcategory utilities, we discovered that cable and internet connections were the most frequently mentioned in the collected data. We then examined the "community features" variable, which contains multiple pieces of data. Upon examination, we classified them as a gated community, pool, playground, etc.

Our paper's empirical methodology relies on the availability of geospatial data, particularly hurricane and hurricane-driven flooding information. According to the literature, proximity to the coast is one of the most influential factors in determining property values in coastal areas[84] (Bin & Kruse, 2006). Consequently, choosing our methodology is contingent on the number of natural disasters a typical Puerto Rican home endures and how this affects the future pricing concerning the available geospatial information.

The wind speed at each house's location determined whether Hurricane Maria struck it. We used the distance between home and the hurricane's path to determine whether housing prices within X miles had a significant hurricane impact. In addition, the flood zone[85] information obtained for each home determines whether such flooding measures affected housing prices in Puerto Rico. Lastly, the distance from the coast will limit any potential ripple effect on housing prices. FEMA's Hazus MH GIS software is the source of all these data.

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[84] ocean, sound, and intracoastal waterways.

[85] The flood zone is the 100-year flood plain.

Using ArcGIS Pro, we retrieved geospatial data based on the location[86] of each house. In addition, we gathered information regarding the distance of parks, railways, airports, and major roads from the geolocation of each residence. Table 2.2 describes the types of spatial variables regarding Hurricane Maria.

Table 2.2. Geospatial characteristics.

Variable	**Description**	**Type**
Wind speed Irma	Sustained wind speed (mph) a house experience during Hurricane Irma.	Continuous
Wind speed Maria	Sustained wind speed (mph) a house experience during Hurricane Maria.	Continuous
Distance to Irma Track	Distance (mile) of each house from the core of Hurricane Irma.	Continuous
Distance to Maria Track	Distance (mile) of each house from the core of Hurricane Maria.	Continuous
Flood zone	The house is in a flood zone or not.	Categorical
Distance to the coastline	Distance (mile) of each house from the coastline.	Continuous
Distance to Airport	Distance (miles) of each house from the nearby major airport	Continuous
Distance to Rail Station	Distance (miles) of each house from the nearby major railway station	Continuous
Distance to Road	Distance (miles) of each house from the nearby primary road	Continuous
Distance to Park	Distance (miles) of each house from the nearby park.	Continuous

Source: ArcGISPro online database.

Table 2.3 display the descriptive statistics of the core variables. In our data sample, there is 1001 home information. The average home sold was $427,000, while the highest price was $8.5 million. A typical residence in Puerto Rico consists of four bedrooms, three bathrooms, and approximately 2,100 square feet of space. With a standard lot size of 6,200 square feet, the annual homeowner's association fee is $70. Each residence is assigned two

[86] Location in our data refers to the address of each house. In case geo mapping is not possible with the physical address, then zip code is used as proxy for location.

parking spaces, and the average age of a home is 38 years. Most homes are on the ground floor and have two full bathrooms.

Table 2.3. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Value ($)	1001	427851.87	824544.01	500	8500000
Bed	1001	3.666	1.109	1	8
Bath	1001	2.764	1.561	1	10
Age of House (Years)	819	37.788	26.21	0	319
Interior area (Sq ft.)	1001	2102.362	1523.058	462	8065
HOA fee ($)	698	70.102	169.992	0	2000
Number of Parking	660	2.211	1.307	1	8
Lot Size (Sq ft.)	794	6199.899	3826.748	435.6	11325.6
Full bathroom	988	2.365	1.237	1	7
Floor	717	1.456	.715	1	4
Windspeed Maria (miles)	1001	90.52	8.533	62	103
Distance from Maria (miles)	1001	11.817	6.485	.444	36.417
Distance from Coast (miles)	1001	5.438	4.086	.197	16.968
Distance from Floodplain (miles)	1001	.462	.651	.003	4.313
Distance from Beach	1001	6.236	4.067	.417	17.44
Dummy 3 miles buffer	1001	.037	.189	0	1
Dummy 6 miles buffer	1001	.178	.383	0	1
Dummy 9 miles buffer	1001	.386	.487	0	1
Dummy 12 miles buffer	1001	.597	.491	0	1
Dummy house location (Right /Left)	1001	.7942058	.4044829	0	1

Again, the average wind speed during Maria's landfall was approximately 90 miles per hour, and each home was located within 12 miles of the storm's path. The moderate residence is within six miles of the beach. In addition, the average distance from the floodplain is 0.5 miles, and the average length of the coastline is less than six miles.

2.4 Findings:

<u>2.4.A. Standard Hedonic Price Model.</u>

<u>2.4.A.1. Base Hedonic Price Determination.</u>

In Table 2.4, we began analyzing the primary Hedonic price determination for homes in Puerto Rico. A simple reduced form of the hedonic model is formulated for this purpose. We denoted it as our base model. We estimated four simple hedonic models to determine the factors influencing home prices. In column (1), we did not control the base model's year and location fixed effects.

Table 2.4. Base/Specific Regression of Single-Family Home in Puerto Rico

	(1) Lvalue	(2) Lvalue	(3) Lvalue	(4) Lvalue
3-bedroom	.29118	.29285	.32036*	.31986*
	(.18124)	(.18098)	(.18003)	(.17974)
4-bedroom	.35804*	.32326*	.37141*	.33408*
	(.19173)	(.19293)	(.19021)	(.19141)
5-bedroom	.10103	.10538	.10547	.10809
	(.22268)	(.22413)	(.22073)	(.22206)
6-bedroom	.2867	.20573	.34135	.26205
	(.28555)	(.28527)	(.28355)	(.28309)
7-bedroom	-.19753	-.22953	-.14661	-.17962
	(.33764)	(.33707)	(.33535)	(.33477)
8-bedroom	-.37143	-.27994	-.33552	-.25482
	(.44375)	(.44254)	(.44069)	(.43917)
Net living area (Sq-ft.)	.00018***	.00018***	.00017***	.00017***
	(.00003)	(.00003)	(.00003)	(.00003)
Bathroom	.35441***	.35018***	.35669***	.3508***
	(.04121)	(.04109)	(.0409)	(.04074)
Age of House	.00301	.00051	.00274	.00005
	(.00192)	(.00203)	(.0019)	(.00202)
HOA fee ($)	.00161***	.00174***	.00164***	.00178***
	(.00024)	(.00025)	(.00024)	(.00025)
Parking (#)	.09022***	.0819***	.09144***	.08361***
	(.02823)	(.02808)	(.028)	(.02783)
Log of lot size (sq-ft.)	.04881	.08263*	.03945	.07404
	(.04634)	(.04727)	(.04602)	(.04689)
East		.10079		.08113
		(.15609)		(.155)
Metro		.28164*		.29374*
		(.15237)		(.1515)
North		-.05518		-.04728
		(.17032)		(.16879)
South		.04217		.04334
		(.17564)		(.17392)
West		-.23179		-.21635
		(.21863)		(.21671)
2019.Year Sold			-.01644	-.10128
			(.57058)	(.56491)
2020.Year Sold			.12691	.08256
			(.56423)	(.55839)
2021.Year Sold			.32451	.26718
			(.56436)	(.55871)
Constant	9.63939***	9.33997***	9.53188***	9.28982***
	(.44489)	(.47879)	(.72407)	(.73887)
Observations	561	561	561	561
R-squared	.60231	.61388	.61151	.62349
Year Fixed Effect	No	No	Yes	Yes
Location Fixed Effect	No	Yes	No	Yes

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (3) are in the log of housing values. X-bedroom is bedroom dummies with the base of one and two bedrooms together. The net living area is the interior area minus the total area of the bedroom in sq-ft.

The dependent variable is not evaluated at a constant price and is the home's sale price in log form at the time of sale. According to column (1) analysis, homes with up to six bedrooms and available net living space[87] increase in value. The number of bathrooms, HOA fees, and parking spaces increased the price.

In column (2), we controlled the location-fixed effects. Puerto Rico's 78 counties are decentralized into six zones to ensure smooth governance. The year-fixed effects are maintained in column (3) to check for a significant departure from the base regression model. Our estimation revealed that independent variables exhibit the same pattern despite the controls. Three- and four-bedroom homes are in high demand on this small island.

In addition, the net living space and the number of bathrooms continue to influence home prices. Due to unobserved heterogeneity between zones, the only deviation we observe is that lot size significantly impacts home prices. Finally, when we enforced both controls in column (4), there were few observed deviations from the previous three regression estimates. A significant finding from these four model estimates is that seven- or eight-bedroom homes would reduce home values in Puerto Rico.

2.4.A.2. Cross-Check of Location Variable's Impact on The Home Value.

The previous subsection underlines significant factors that contributed to the home values. In addition to that analysis, we wanted to investigate whether certain location variables affect home values. Hence, we added specific county-level characteristics to the estimation results in Table 2.5. Column (1) estimations contain the same base hedonic specification as Table 2.4. For column (2) outcomes, we regress flood and disaster-related

[87] Net living area is the difference between the interior area and bedroom size. For the sake simplicity we skipped bathroom and kitchen area from it.

variables. One key objective was finding whether homes in a 100-year floodplain impacted home values. The significant log-linear flood coefficient (-0.464376) implies that a home located in a 100-year flood plain decreased the home value by 37.14 percent.

Table 2.5. Impact of location variables on Puerto Rican home value.

	(1) Lvalue	(2) Lvalue	(3) Lvalue	(4) Lvalue
3-bedroom	.319859*			.288263
	(.17974)			(.189942)
4-bedroom	.334078*			.335435*
	(.191414)			(.201917)
5-bedroom	.108093			.100252
	(.222059)			(.232526)
6-bedroom	.262047			.268041
	(.283091)			(.290863)
7-bedroom	-.17962			-.214514
	(.334769)			(.341325)
8-bedroom	-.25482			-.140909
	(.439173)			(.443505)
Net living area (Sq-ft.)	.000166***			.000147***
	(.000034)			(.000035)
Bathroom	.350803***			.31193***
	(.040736)			(.042767)
Age of House	.000055			-.001754
	(.002018)			(.002091)
HOA fee ($)	.001777***			.001568***
	(.00025)			(.000258)
Parking (#)	.083606***			.074156***
	(.027826)			(.028095)
Log of lot size (sq-ft.)	.074039			.087163*
	(.046886)			(.048323)
In Flood-zone		-.464376***		.021088
		(.101134)		(.100205)
Distance from Maria		.038896***		.003561
		(.009826)		(.009463)
Distance from Coast		-.121965***		.032417
		(.042182)		(.040824)
Distance from Floodplain		-.190738***		.002668
		(.066579)		(.06165)
Distance from beach		.096126**		-.050737
		(.043741)		(.041158)
Median-HH-income			.000015***	4.000e-06
			(4.000e-06)	(4.000e-06)
Vacant Units			.000376***	.000271**
			(.000097)	(.00013)
Homeownership rate			-.01578***	-.005231
			(.003231)	(.003602)
Median Rent			.00175***	.000496*
			(.000272)	(.000291)
Airport distance			-8.000e-06	-.000012
			(.000011)	(.00001)
Railway distance			7.000e-06*	0

			(4.000e-06)	(4.000e-06)
Major road distance			-9.000e-06	.000039
			(.000025)	(.000025)
Park distance			-4.000e-06	5.000e-06
			(8.000e-06)	(7.000e-06)
Constant	9.2898***	6.855***	11.887***	9.878***
	(.738866)	(.986429)	(.302695)	(1.18838)
Observations	561	1001	960	535
R-squared	.623485	.204215	.309181	.651689

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (3) are in the log of housing values. X-bedroom is bedroom dummies with the base of one and two bedrooms together. The net living area is the interior minus the total bedroom area in sq-ft. Year and location fixed effects controlled.

Similarly, the significance of distance from the coast coefficient confirmed that houses near the beach are more expensive than those further away. Distance from Hurricane Maria's track suggested that their prices will rise when homes are away from the track. The distance from the beach is significant, but its positive sign contradicts that. It implies that when a home is far away from the beach, the price of a house will increase.

Column (3) examines the role of community information and proximity to local amenities in determining home prices. For example, median household income positively impacts home prices, whereas median rent and the vacancy rate have a negative impact. It is expected that a house near a railway station will have a premium on home value. When the disaster, location, and community preference merged in column (4), only the median rent and vacant units pushed up home values in Puerto Rico.

2.4.A.3. Profiling The Impact of Hurricane Maria on Home Values.

The overall goal of this project is to determine how hurricane exposure affects home values in Puerto Rico. We used a hedonic regression with key Hurricane Maria characteristics, such as hurricane wind speed and house distance from hurricane Maria track to validate that goal. Additional spatial variables such as flood zone, distance from

Table 2.6. Impact of Hurricane Maria on Puerto Rican home value.

	(1) Lvalue	(2) Lvalue	(3) Lvalue
3-bedroom	.31986*	.32347*	.35751**
	(.17974)	(.17968)	(.18045)
4-bedroom	.33408*	.33487*	.35246*
	(.19141)	(.19105)	(.19119)
5-bedroom	.10809	.10563	.11016
	(.22206)	(.22232)	(.2221)
6-bedroom	.26205	.22376	.23857
	(.28309)	(.28305)	(.28237)
7-bedroom	-.17962	-.21057	-.18783
	(.33477)	(.33451)	(.33316)
8-bedroom	-.25482	-.22796	-.19029
	(.43917)	(.43779)	(.43662)
Net living area (Sq-ft.)	.00017***	.00017***	.00017***
	(.00003)	(.00003)	(.00003)
Bathroom	.3508***	.34317***	.34803***
	(.04074)	(.04118)	(.04094)
Age of House	.00005	-.00097	-.00083
	(.00202)	(.00203)	(.00203)
HOA fee ($)	.00178***	.00171***	.00173***
	(.00025)	(.00025)	(.00025)
Parking (#)	.08361***	.07875***	.08439***
	(.02783)	(.02785)	(.02794)
Log of lot size (sq-ft.)	.07404	.08666*	.0893*
	(.04689)	(.04691)	(.04663)
Maria windspeed		.0033	-.00222
		(.00885)	(.01445)
In Flood-zone		.02144	.50306
		(.08883)	(2.71333)
Distance from Maria		.00301	.00612
		(.00875)	(.07168)
Distance from Coast		.01202	.04211
		(.0379)	(.04036)
Distance from Floodplain		-.02433	-.03709
		(.05941)	(.06009)
Distance from beach		-.04174	-.06119
		(.0393)	(.04097)
FldZone#distomaria			-.14761
			(.11779)
distomaria#mariamaxsu			.00009
			(.00084)
FldZone#mariamaxsu			-.00448
			(.02878)
FldZone#distomaria#mariamaxsu			.00163
			(.00137)
Constant	9.28982***	9.39919***	9.63235***
	(.73887)	(1.13519)	(1.45623)
Observations	561	561	561
R-squared	.62349	.63219	.63991

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (3) are in the log of housing values. X-bedroom is bedroom dummies with the base of one and two-bedroom together. The net living area is the interior area minus the total area of the bedroom in sq-ft. Year and location fixed effects are controlled.

the beach, coast, and floodplains are included in column (2) to calculate the net effect of Hurricane Maria. We tested the interactions between the hurricane and spatial variables in column (3).

There are no notable findings in column 2 from the estimated results of the hurricane exposure variables. None of them seemed to affect the home's value significantly. Furthermore, it is worth noting that Maria's wind speed and distance from the track had an adverse effect on the price. The negative coefficient of house age indicates that older homes cost less and is the only notable departure from the base regression.

We also investigated whether interactions between Hurricane Maria variables and the flood zone hurt home values. Our findings in column (3) indicate that homes within the flood zone's closed boundaries and Maria track could lower prices. Again, being in a flood zone and exposed to a higher hurricane wind category can reduce the value of the affected homes. When the three variables interacted, we expected a significant negative impact on home values, but estimates revealed the opposite. We introduced buffer-specific analysis in the following sub-section because we could not find a compelling repercussion of Hurricane Maria variables.

2.4.A.4. In-Depth Investigation of Hurricane Distance Tract.

The previous subsection brought no conclusive findings based on the hurricane Maria variables. We subgroup the homes into a three-mile buffer to determine the hurricane effect on Puerto Rico's home values. Hence, we limit our buffer up to 12 miles with 3 miles apart. The objective is to verify that buffer-specific analysis can capture the variations that were not feasible in the actual hurricane distance track. These 3-mile buffers are randomly assigned, and we also checked for a one-mile difference in our treatment analysis. The buffer zones then interacted with the zone variable and houses located on the right or left side of the hurricane. We want to determine which homes Maria severely hit in Puerto Rico. We report the estimated results in Table 2.7. Each column represents a 3, 6, 9, and 12[88] miles buffer.

The findings in column 1 are intriguing. The first effect is a decrease in the value of homes within a three-mile buffer. Second, southern and western houses lost value regardless of hurricane track distance or location. Furthermore, Hinojosa & Meléndez (2018) reported that the Hurricane Maria tract's left side house was severely impacted, with a powerful impact in the northern-western counties. According to our findings, Maria ravaged the left side house in northern Puerto Rico within the three-mile buffer. This left north combination harms all buffer levels.

The six and 9-mile buffer regression results are shown in columns (2) and (3). When a house is located on Puerto Rico's western side, the hurricane effect in a 6-mile buffer is negative and significant. The three-variable interaction was also insignificant but negative. Homes within the nine-mile buffer had negative coefficients, but the left-side interaction term did not produce the expected results. In the 12-mile buffer zone, we observed a similar pattern. As a result, we can conclude that hurricane Maria's impact is felt most strongly within 6 miles of the track and on homes on the left.

Table 2.7. Triple interaction between distance buffer, price of a house, and region.

	(1)	(2)	(3)	(4)
	3-miles buffer Lvalue	6-miles buffer Lvalue	9-miles buffer Lvalue	12-miles buffer Lvalue
3-bedroom	.31354*	.31891*	.32052*	.35144*
	(.18328)	(.17621)	(.18298)	(.17972)
4-bedroom	.32071	.35425*	.32071*	.3581*
	(.19522)	(.18739)	(.19389)	(.19127)
5-bedroom	.08713	.12646	.10069	.11977

[88] 12 miles limit selected based on the mean distance from the Hurricane Maria track.

	(.22556)	(.21762)	(.22548)	(.22194)
6-bedroom	.2308	.20542	.23525	.2715
	(.28608)	(.27716)	(.28485)	(.28231)
7-bedroom	-.23054	-.19805	-.21992	-.22451
	(.33981)	(.32726)	(.33641)	(.33332)
8-bedroom	-.18166	-.26887	-.06422	-.12064
	(.44621)	(.43332)	(.45115)	(.44485)
Net living area (Sq-ft.)	.00016***	.00017***	.00017***	.00016***
	(.00003)	(.00003)	(.00003)	(.00003)
Bathroom	.35801***	.35219***	.34808***	.35138***
	(.04118)	(.04011)	(.04132)	(.04098)
Age of House	.00039	.00024	.00033	-.00088
	(.00205)	(.002)	(.00205)	(.00207)
HOA fee ($)	.00182***	.00154***	.0018***	.00179***
	(.00026)	(.00027)	(.00025)	(.00025)
Parking (#)	.08575***	.08784***	.08968***	.09043***
	(.02827)	(.02751)	(.0282)	(.02803)
Log of lot size (sq-ft.)	.07938*	.08517*	.08111*	.08334*
	(.04746)	(.04615)	(.04751)	(.04696)
3-miles buffer	-.46783			
	(.82616)			
East	.03113	.02514	-.05806	-.04669
	(.77261)	(.75212)	(.77638)	(.77085)
Metro	.24136	.26267	.27466	.46744
	(.77233)	(.75069)	(.77135)	(.76887)
North	-.14435	.03436	.2162	.3333
	(.77537)	(.75873)	(.92296)	(.31722)
South	-.09021	-.07589	-.15664	-.28111
	(.19471)	(.1988)	(.28145)	(.55125)
West	-1.34576	-1.38087	-1.352	-1.35623
	(1.08529)	(1.05453)	(1.08291)	(1.07521)
3-miles#East	.44166			
	(.87896)			
3-miles#North	.70998			
	(.90427)			
Left Side Home (LSH)	.08437	.04164	.16188	.32216
	(.78532)	(.76597)	(.80841)	(.93172)
3-miles#LSH	.14003			
	(1.00258)			
East# LSH	-.0787	-.27777	-.41431	-.42469
	(.87959)	(.70487)	(.65677)	(.64355)
North# LSH	-.00004	-.09198	-.35983	-.3535
	(.83678)	(1.07981)	(.44715)	(.42455)
West# LSH	1.04968	1.36826	1.08885	.74643
	(1.11046)	(1.08224)	(1.13446)	(1.22708)
3-miles#North#LSH	-.1679			
	(1.18814)			
6-miles buffer		-.4873		
		(.8027)		
6-miles#East		.43303		
		(.81708)		
6-miles#Metro		.05372		
		(.81825)		
6-miles#North		.14275		
		(.82682)		
6-miles#West		-2.68207***		

		(.67719)		
6-miles#LSH		.39702		
		(.8872)		
6-miles#North#LSH		-.08221		
		(1.20399)		
9-miles buffer			-.49032	
			(.82447)	
9-miles#East			.6165	
			(.83846)	
9-miles#Metro			.29756	
			(.83281)	
9-miles#North			.14814	
			(.86598)	
9-miles#South			-.21744	
			(.55914)	
9-miles#West			-.14446	
			(.47931)	
9-miles#LSH			.31032	
			(.88411)	
12-miles buffer				-.45237
				(.8186)
12-miles#East				.57495
				(.8325)
12-miles#Metro				.12807
				(.82617)
12-miles#South				-.00618
				(.63462)
12-miles#West				.42882
				(.65959)
12-miles#LSH				.16166
				(.99072)
_cons	9.28204***	9.20971***	9.29875***	9.26567***
	(1.05896)	(1.02843)	(1.05694)	(1.04837)
Observations	561	561	561	561
R-squared	.62751	.64976	.63053	.63508

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (3) are in the log of housing values. X-bedroom is a bedroom dummy with the base of one and two-bedroom together. The net living area is the interior area minus the total area of the bedroom in sq-ft. Year and location fixed effects controlled.

2.4.A.5. Hurricane Maria's Effect on Pricey Houses.

This subsection used a different criterion to find homes in specific price ranges that Hurricane Maria impacted. We use our sample's mean value of approximately $400,000 for this purpose. The houses are then classified as high-priced if they cost more than $400,000. This classification helps us to check if higher-end homes (which are supposed to have better infrastructure) experienced a price drop because of the hurricane. We tested the interaction using the house's relative location and a 3-mile buffer in Table 2.8.

Table 2.8. Interdependency between distance buffer, location, and expensive homes.

	(1) Lvalue	(2) Lvalue	(3) Lvalue	(4) Lvalue
3-bedroom	.33426**	.31972**	.32192**	.35502**
	(.15525)	(.15214)	(.15526)	(.15265)
4-bedroom	.34301**	.34889**	.34049**	.37287**
	(.16532)	(.1619)	(.16456)	(.16257)
5-bedroom	.18871	.1569	.17874	.20779
	(.19157)	(.18822)	(.19131)	(.18857)
6-bedroom	.10942	.07395	.10822	.12356
	(.24388)	(.24013)	(.24371)	(.2408)
7-bedroom	-.04041	-.05479	-.03362	-.02414
	(.28793)	(.28343)	(.28763)	(.28441)
8-bedroom	.18091	.22082	.23615	.23633
	(.37861)	(.37305)	(.37951)	(.37547)
Net living area (Sq-ft.)	.00008***	.00008***	.00008***	.00008***
	(.00003)	(.00003)	(.00003)	(.00003)
Bathroom	.21198***	.21291***	.20951***	.20979***
	(.03667)	(.03619)	(.03685)	(.03652)
Age of House	-.00257	-.00226	-.00245	-.00344*
	(.00174)	(.00172)	(.00175)	(.00176)
HOA fee ($)	.00102***	.00096***	.00101***	.00118***
	(.00023)	(.00023)	(.00024)	(.00023)
Parking (#)	.05506**	.05627**	.05435**	.04293*
	(.02408)	(.02377)	(.02426)	(.02411)
Log of lot size (sq-ft.)	.05825	.06087	.05768	.0588
	(.04024)	(.04012)	(.0403)	(.03983)
3-miles buffer	.11215			
	(.17597)			
Pricey home (PH)	1.48622***	1.478***	1.48663***	1.82656***
	(.10662)	(.10709)	(.12329)	(.14744)
Left Side Home (LSH)	.31189	.72643***	.43378*	.42768*
	(.18946)	(.22058)	(.22086)	(.23742)
3-miles#PH	-.40583			
	(.35301)			
PH#LSH	-.3595	-.51049	-.43793	-.7953**
	(.29217)	(.31277)	(.35625)	(.36491)
6-miles buffer		-.0488		
		(.08571)		
6-miles#PH		-.79332		
		(.66599)		
6-miles#LSH		-.83203***		
		(.24462)		
6-miles#PH#LSH		2.20867**		
		(1.01349)		
9-miles buffer			.0058	
			(.08057)	
9-miles#PH			-.02389	
			(.17254)	
9-miles#LSH			-.30848	
			(.19377)	

9-miles#PH#LSH			.32351	
			(.61714)	
12-miles buffer				.09273
				(.07842)
12-miles#PH				-.58544***
				(.17108)
12-miles#LSH				-.29233
				(.19457)
12-miles#PH#LSH				.83008
				(.60948)
_cons	9.72617***	9.51044***	9.79392***	9.83149***
	(.65188)	(.64893)	(.65082)	(.64514)
Observations	561	561	561	561
R-squared	.72705	.73516	.7279	.73289

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (3) are in the log of housing values. X-bedroom is a bedroom dummy with a base of one and two bedrooms. The net living area is the interior area minus the total area of the bedroom in sq-ft. Year and location fixed effects controlled.

Table 2.8 reveals two critical findings. The value of the affected expensive home on Maria's track has decreased, and the relationship is significant at the 12-mile buffer column. However, the results revealed that home prices rose when we combined the distance buffer, left side dummy, and the expensive home dummy. Apart from these two findings, the left dummy and buffer zones yielded equivalent results.

2.4.A.6. Exploration Of Home Value with Property Level.

A hurricane is a natural disaster caused by intense winds. Between 2013 and 2020, typhoon-affected high-rise house prices in Shenzhen, China, dropped by 0.8 to 1.2 percent compared to low-rise houses, according to Kong & Liu (2022). Motivated by this recent discovery, we ran two tests to see if homes in Puerto Rico had suffered the same fate. We interacted with hurricane-related variables to see if the flood zone affected the upper story and ground floor homes.

Column (1) of Table 2.9A shows the base regression with the usual distance buffers. Then, in columns (2) through (5), the high story (HS)[89] dummy is introduced, along with

[89] For HS dummy we considered home above the ground floors.

the distance buffer and left side dummy variables. The HS dummy raises the value of the house. The homes on the upper floors are most likely to have an ocean view. We are interested to see what happens to home value when the HS homes are on the left side or within a specific buffer zone.

Table 2.9A. Interdependency between distance buffer, location, and higher stories.

	(1) Lvalue	(2) Lvalue	(3) Lvalue	(4) Lvalue	(5) Lvalue
3-bedroom	.33342*	.32495*	.31573*	.27963	.33907*
	(.17848)	(.18246)	(.17636)	(.18099)	(.17821)
4-bedroom	.37935**	.3366*	.36175*	.29315	.35417*
	(.19036)	(.19727)	(.19045)	(.19461)	(.19257)
5-bedroom	.12674	.10097	.10112	.04429	.07888
	(.22058)	(.2277)	(.22071)	(.22562)	(.22323)
6-bedroom	.2667	.23105	.16578	.14627	.18479
	(.28074)	(.28415)	(.27657)	(.28254)	(.27991)
7-bedroom	-.16074	-.19489	-.17468	-.25941	-.245
	(.33121)	(.33862)	(.32908)	(.3349)	(.33276)
8-bedroom	-.2611	-.27036	-.31012	-.17029	-.16981
	(.43639)	(.43686)	(.42389)	(.43198)	(.42883)
Net living area (Sq-ft.)	.00016***	.00016***	.00016***	.00017***	.00016***
	(.00003)	(.00003)	(.00003)	(.00003)	(.00003)
Bathroom	.34485***	.35331***	.35***	.34952***	.3518***
	(.04034)	(.0405)	(.03964)	(.04042)	(.04022)
Age of House	-.0005	.00119	.00143	.00138	.0002
	(.00203)	(.002)	(.00196)	(.00199)	(.00202)
HOA fee ($)	.00156***	.00188***	.00164***	.00191***	.00193***
	(.00026)	(.00025)	(.00025)	(.00025)	(.00025)
Parking (#)	.08251***	.10735***	.1062***	.10178***	.09665***
	(.02761)	(.02816)	(.02749)	(.02802)	(.02795)
Log of lot size (sq-ft.)	.08202*	.1006**	.11457**	.09784**	.09507**
	(.04646)	(.04675)	(.04564)	(.04639)	(.04618)
3-miles buffer	.17232				
	(.17705)				
6-miles buffer	-.3796***				
	(.11233)				
9-miles buffer	.16477				
	(.11376)				
12-miles buffer	-.16379*				
	(.09732)				
Higher stories (HS)		.00606	.08405	.12967	.31372**
		(.0902)	(.0939)	(.1125)	(.14812)
Left Side Home (LSH)		.43939*	.61777**	.75695***	.67436**
		(.23049)	(.2684)	(.27894)	(.29156)
Higher stories #LSH		-.23358	-.21027	-.37453	-.54895*
		(.20296)	(.21722)	(.27395)	(.32983)
3-miles buffer		.01847			
		(.26573)			
HS#3-miles buffer		-.0621			
		(.36487)			
LSH#3-miles buffer		-.20611			

		(.4477)			
6-miles buffer			-.09447		
			(.11236)		
HS#6-miles buffer			-.47219**		
			(.18709)		
LSH#6-miles buffer			-.4852		
			(.31856)		
HS#LSH#6-miles buffer			-.15839		
			(.48129)		
9-miles buffer				.02655	
				(.10194)	
HS#9-miles buffer				-.27326*	
				(.14972)	
LSH#9-miles buffer				-.56554**	
				(.27699)	
HS#LSH#9-miles buffer				.45154	
				(.39702)	
12-miles buffer					-.02533
					(.10012)
HS#12-miles buffer					-.41994**
					(.16262)
LSH#12-miles buffer					-.35367
					(.25324)
HS#LSH#12-miles buffer					.52044
					(.40159)
Constant	9.32493***	8.72888***	8.57889***	8.76011***	8.85916***
	(.73557)	(.74907)	(.73626)	(.74174)	(.73918)
Observations	561	538	538	538	538
R-squared	.63434	.63305	.65089	.63925	.64263

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (3) are in the log of housing values. X-bedroom is bedroom dummies with the base of one and two bedrooms together. The net living area is the interior area minus the total area of the bedroom in sq-ft. Year and location fixed effects controlled.

The upper-story home may be more vulnerable to hurricane Maria if located on the left side of the track. In the last column, we noticed that the prices of the higher-story homes on the left side have significantly decreased in value. The buffer distance does not affect this development. Furthermore, the interaction between high-story houses and buffer zones (3,6,9,12 miles) indicated that home value declined; these interactions were significant between 6 and 12 miles of the buffer. Finally, when a high-story home is located on the left side and within 6 miles of the buffer, the triple interaction between the variables appears to have a declining effect on price.

The upper-floor homes may not be prone to flooding, but the ground floors are. We assume that a home in a 100-year-old flood plain is at a higher risk of being flooded by a hurricane. As a result of this strategy, we investigated the possibility of a flood zone interacting with first-floor homes. In Table 2.9B, we added a buffer distance dummy and a left side dummy to the analysis to capture more variation in the home values. The first-floor home in a flood zone faced downward pressure in its value. Surprisingly, a first-floor home in the flood zone and on the left side of the track did not yield the expected results. The first-floor homes had no interaction with the distance buffer.

Table 2.9B. Flood zone effect on the first-floor homes and relative location from Maria.

	(1) Lvalue	(2) Lvalue	(3) Lvalue	(4) Lvalue
3-bedroom	.366034**	.352429**	.363115**	.371739**
	(.182093)	(.179299)	(.18094)	(.180072)
4-bedroom	.361955*	.371606*	.353894*	.36621*
	(.196474)	(.193564)	(.195472)	(.194452)
5-bedroom	.150067	.140596	.140929	.140579
	(.228686)	(.224969)	(.227177)	(.226035)
6-bedroom	.289363	.260625	.271606	.279536
	(.284525)	(.280641)	(.283415)	(.281832)
7-bedroom	-.126331	-.115675	-.132953	-.136307
	(.337225)	(.333212)	(.33634)	(.334775)
8-bedroom	-.243139	-.224451	-.190875	-.183501
	(.433945)	(.428895)	(.434169)	(.431441)
Net living area (Sq-ft.)	.000163***	.000161***	.000165***	.000165***
	(.000034)	(.000034)	(.000034)	(.000034)
Bathroom	.349832***	.345151***	.3478***	.348177***
	(.041026)	(.040572)	(.040947)	(.040742)
Age of House	.00129	.001308	.001178	.000417
	(.002006)	(.001983)	(.002002)	(.002018)
HOA fee ($)	.001883***	.001681***	.001886***	.00188***
	(.000252)	(.000254)	(.000249)	(.000248)
Parking (#)	.10784***	.109048***	.106994***	.105905***
	(.028352)	(.028012)	(.028273)	(.028147)
Log of lot size (sq-ft.)	.106381**	.113159**	.108205**	.10877**
	(.047005)	(.046481)	(.046887)	(.046663)
Airport distance	-.000012	-.000012	-.000012	-.000012
	(9.000e-06)	(9.000e-06)	(9.000e-06)	(9.000e-06)
Railway distance	-1.000e-06	-1.000e-06	-1.000e-06	-1.000e-06
	(4.000e-06)	(4.000e-06)	(4.000e-06)	(4.000e-06)
Major road distance	.000035	.000038	.000036	.000033
	(.000024)	(.000024)	(.000024)	(.000024)
Park distance	1.000e-06	1.000e-06	2.000e-06	2.000e-06
	(7.000e-06)	(7.000e-06)	(7.000e-06)	(7.000e-06)
3-miles buffer	-.028217			
	(.170058)			
Flood Zone (FZ)	.22105	.205073	.237304*	.275053**
	(.139183)	(.137191)	(.138669)	(.139091)
First Floor (FF)	.023761	.045407	.036116	.04228
	(.097534)	(.096355)	(.097329)	(.096836)
FZ#FF	-.123338	-.163408	-.161206	-.217106
	(.181205)	(.179391)	(.182222)	(.183166)
Left Side Home (LSH)	.220993	.217902	.232681	.261193

	(.240317)	(.233887)	(.236065)	(.235281)
FZ#LSH	-.730259	-.706405	-.815694	-.920916
	(.795101)	(.78553)	(.794478)	(.79219)
FF#LSH	.177158	.16381	.144941	.141392
	(.2085)	(.204513)	(.20716)	(.20578)
FZ#FF#LSH	.786973	.828399	.888354	.977324
	(.838358)	(.828636)	(.838658)	(.835365)
6-miles buffer		-.316059***		
		(.091353)		
9-miles buffer			-.131189	
			(.083284)	
12-miles buffer				-.211094***
				(.078648)
_cons	8.696502***	8.721898***	8.769407***	8.862316***
	(.764728)	(.752404)	(.761248)	(.758723)
Observations	538	538	538	538
R-squared	.638252	.646609	.640001	.643321

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (3) are in the log of housing values. X-bedroom is a bedroom dummy with a base of one and two bedrooms. The net living area is the interior area minus the total area of the bedroom in sq-ft. Year and location fixed effects controlled.

2.4.A.7. Profiling The Impact of Hurricane Wind Levels and Age on Housing Values.

Home values appear to be affected by exposure to hurricane-force winds. Zivin et al. (2020) conducted a recent study on hurricane exposure and determined whether a location was within a 64-knot wind speed circle and severely exposed to 96-knot winds. Based on the Saffir-Simpson Hurricane Wind Scale, we used a similar strategy and divided the house into three categories. The distinctions are most noticeable between homes subjected to tropical storm winds and those subjected to category one and two windspeeds.

According to hedonic literature, a home's value decreases as it ages. Some of the houses on Zillow are more than 300 years old. As a result, we divided homes into four categories based on their age: less than 20 years old, 21-40 years old, 41-60 years old, and more than 60 years old. We then gave them a buffer distance to interact with to see if adding more layers of information could yield meaningful results.

Table 2.10 have five columns. Column (1) shows the base regression with the dummies or buffer distances. Category one and two levels of wind are expected to decrease the home without interaction, with category two having a slightly higher impact. House values dropped significantly between the ages of 21 and 60. The effect of the other coefficient remained constant.

With a 3-mile buffer distance, we interacted with age and wind speed variables in column (2). There was no significant relationship between age and wind category, except an unsettling finding that homes older than 60 faced categories one and two wind increased in value. Again, category-2 wind exposure to a home within a 3-mile radius reduces the home's value. Other noteworthy findings include the possibility that home values between 41 and 60 years old and exposed to category one wind are low within the 3-mile buffer distance.

Table 2.10. Interaction between windspeed, age of the house, and buffer zone.

	(1)	(2)	(3)	(4)	(5)
	Lvalue	Lvalue	Lvalue	Lvalue	Lvalue
3-bedroom	.37927**	.34817*	.36075**	.29485	.29802
	(.17577)	(.18736)	(.18236)	(.18638)	(.18297)
4-bedroom	.40326**	.35595*	.4055**	.30479	.29742
	(.18704)	(.19764)	(.19259)	(.196)	(.1935)
5-bedroom	.20423	.19461	.20866	.13834	.12758
	(.21804)	(.22955)	(.22489)	(.22811)	(.22437)
6-bedroom	.38676	.34721	.37309	.27281	.28112
	(.27664)	(.2865)	(.28103)	(.28679)	(.28249)
7-bedroom	-.02788	-.1025	-.03367	-.1097	-.09335
	(.32744)	(.34059)	(.33302)	(.33792)	(.33384)
8-bedroom	-.18648	-.03675	-.11381	-.21298	-.21217
	(.42958)	(.45947)	(.43532)	(.43969)	(.43415)
Net living area (Sq-ft.)	.00015***	.00015***	.00014***	.00015***	.00015***
	(.00003)	(.00003)	(.00003)	(.00003)	(.00003)
Bathroom	.31655***	.32304***	.31419***	.32201***	.31489***
	(.04066)	(.04149)	(.04095)	(.04157)	(.04119)
Age of House	.00152***	.00183***	.00157***	.00181***	.00182***
	(.00025)	(.00025)	(.00025)	(.00025)	(.00025)
HOA fee ($)	.07881***	.08051***	.08067***	.06991**	.06417**
	(.02738)	(.02804)	(.02753)	(.02794)	(.02783)
Parking (#)	.06474	.07361	.07151	.07146	.07582
	(.04613)	(.04694)	(.04631)	(.04697)	(.04662)
Airport distance	-.00001	-.00001	-.00001	-.00001	-.00001
	(.00001)	(.00001)	(.00001)	(.00001)	(.00001)
Railway distance	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)
Major road distance	.00005**	.00004*	.00005**	.00005**	.00004*
	(.00002)	(.00002)	(.00002)	(.00002)	(.00002)
Park distance	.00001	.00001	.00001	.00001	0
	(.00001)	(.00001)	(.00001)	(.00001)	(.00001)
3-miles buffer	.18099	-.80998			

	(.17439)	(1.14658)			
6-miles buffer	-.42323***		-.63412		
	(.1142)		(.93826)		
9-miles buffer	.13318			-1.22512	
	(.11212)			(.8535)	
12-miles buffer	-.07166				-1.24209
	(.10079)				(.84597)
Category-1 Wind (C1W)	-.0629	-.40395	-.37515	-.50722	-.47093
	(.17127)	(.33523)	(.33192)	(.36464)	(.36703)
Category-2 Wind (C2W)	-.09064	-.16846	-.2583	-.43192	.05603
	(.18907)	(.35755)	(.36148)	(.43662)	(.51983)
21-40 Years Old	-.24062***	-.68258*	-.74023*	-.89402**	-.92854**
	(.0883)	(.38355)	(.37896)	(.41198)	(.41401)
41-60 Years Old	-.35085***	-.46511	-.51196	-.56509	-.55972
	(.10212)	(.40288)	(.39782)	(.43194)	(.43913)
60+ Years Old	.35216*	-.97198	-.98343	-1.14514	-1.14497
	(.18485)	(.8244)	(.81401)	(.83415)	(.82725)
C1W#21-40 Years		.51159	.46501	.57177	.54143
		(.4001)	(.40061)	(.43987)	(.45069)
C1W#41-60 Years		.28752	.18999	.23439	.29413
		(.4182)	(.41776)	(.45932)	(.47717)
C1W#60+ Years		1.50086*	1.41579*	1.53913*	1.52158*
		(.85109)	(.84397)	(.86729)	(.86513)
C2W#21-40 Years		.38461	.39519	.48255	-.21537
		(.41837)	(.41737)	(.49606)	(.60576)
C2W#41-60 Years		-.04461	-.05327	-.01861	-.77227
		(.43254)	(.4309)	(.505)	(.6192)
C2W#60+ Years		1.50447*	1.67435*	1.8371*	1.64502
		(.90549)	(.91311)	(.95228)	(1.01622)
C1W#3-miles buffer		.83769			
		(1.18153)			
C2W#3-miles buffer		-.07735			
		(.9814)			
21-40 Years#3-miles		.53127			
		(.79856)			
41-60 Years#3-miles		-.31721			
		(.96381)			
60+ Years#3-miles		-.26449			
		(1.02921)			
C1W#21-40#3-miles		-.27949			
		(.89731)			
C1W#41-60#3-miles		.31175			
		(1.07571)			
C1W#6-miles buffer			.08219		
			(.95149)		
C2W#6-miles buffer			.10808		
			(.89362)		
21-40 Years#6-miles			.32662		
			(.48503)		
41-60 Years#6-miles			-.68826		
			(.81759)		
60+ Years#6-miles			-.65369		
			(.71573)		
C1W#21-40#6-miles			.00809		

			(.53357)		
C1W#41-60#6-miles			1.02125		
			(.85114)		
C1W#60+#6-miles			.26917		
			(1.0732)		
C1W#9-miles buffer				.89901	
				(.87047)	
C2W#9-miles buffer				1.09982	
				(.90013)	
21-40 Years#9-miles				1.14477	
				(1.0169)	
41-60 Years#9-miles				.46479	
				(1.16997)	
60+ Years#9-miles				-1.00847	
				(.71865)	
C1W#21-40#9-miles				-.88781	
				(1.03695)	
C1W#41-60#9-miles				-.25979	
				(1.18829)	
C1W#60+#9-miles				.41552	
				(1.08405)	
C2W#21-40#9-miles				-.86794	
				(1.07573)	
C2W#41-60#9-miles				-.25362	
				(1.22313)	
C1W#12-miles buffer					.94493
					(.86428)
C2W#12-miles buffer					.61852
					(.93517)
21-40 Years#12-miles					1.2719
					(.97336)
41-60 Years#12-miles					.78463
					(1.04679)
60+ Years#12-miles					-.711
					(.73415)
C1W#21-40#12-miles					-.96375
					(.99733)
C1W#41-60#12-miles					-.74239
					(1.07499)
C1W#60+#12-miles					.07871
					(1.08659)
C2W#21-40#12-miles					-.24623
					(1.08311)
C2W#41-60#12-miles					.19977
					(1.14859)
Constant	9.66236***	10.02405***	10.03609***	10.30401***	10.30391***
	(.74309)	(.80083)	(.7895)	(.80855)	(.80367)
Observations	561	561	561	561	561
R-squared	.65431	.65266	.66207	.65593	.6617

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (5) are in the log of housing values. X-bedroom is a bedroom dummy with a base of one and two bedrooms. The net living area is the interior minus the total bedroom area in sq-ft. Year and location fixed effects controlled.

We list the homes within a 6-mile buffer zone, their age, and wind speed in column one (3). Apart from the 41-60 year and 60+ year homes in a 6-mile buffer, the rest of the dual buffer interaction has no discernible impact on home value. Furthermore, the age, wind, and distance buffers did not produce the expected home value reductions. In column (4), we found that 60+-year-old homes within the 9-mile buffer zone may lower home prices. Furthermore, the triple interaction term of Cat-1 winds and 41-60-year-old homes within the 9-mile buffer zone lowered house prices in Puerto Rico. The combined differential impact may diminish as we move beyond the 9-mile buffer zone. When a home reaches 60 years old, a house within a 12-mile radius may be less expensive.

On the other hand, home age at 21-40 years could reduce housing value when exposed to category one and two wind levels. The only disadvantage of this part of the regression is that we did not obtain any significant results regarding the triple interaction. Nonetheless, we take credit for identifying some excellent results combined with age and windspeed.

2.4.A.8. Robustness Check of The Housing Price in Puerto Rico.

In Table 2.11, we tested the robustness of our findings. Six regression models are estimated using the most detailed data available. Column 1 shows our base hedonic price model. According to the preliminary results, three and four-bedroom homes are the most popular among potential buyers in Puerto Rico. Increased net living areas, parking spaces, bathrooms, and HOA fees increase home values. We added a dummy variable for construction, floor, foundation, and roof material to determine which types of materials control home values to the column (2) regression. Only the home built with slab foundations increased home price, while most material decreased home value. That could imply that the construction material used is not a significant factor for home prices in Puerto Rico. This finding is somewhat perplexing because, according to the literature, these construction variables were expected to raise the home price.

We added additional home feature dummy variables (from the literature) in column (3) that should work as premium for home values. The variables are homes equipped with hurricane shutters, a water view, a house located in a gated community, a swimming pool and park, and a balcony or not. The home values increased by 70 percent more when doors and windows were equipped with hurricane shutters. Similarly, homes with a pleasant water view would augment the price by 76 percent. Gated community homes sold 120 percent more than their base value, and featuring a pool similarly enhances the value. The presence of a playground increased prices, too, whereas a home with a balcony and park sells lower than the original listed price. In column (4), we regressed the distance from a major road, railway station, park, airport, and beach on the home values. Estimates from the beach distance suggest buying a house away from the beach reduces the home value by 5.5 percent.

We ran two robust regressions. For the first robust regression model in column (5), we considered the home construction materials, additional home features, and distances from amenities. In the first robust model, we noticed some variables shift their signs. Construction materials, for example, pushed up prices rather than lower them. Aside from that, gated community homes sell for 60% more, and distance from major roads increases prices significantly. Moving away from the coast lowered the cost of living in Puerto Rico. Finally, we entered the county-level data in column (6). In addition to the previously mentioned findings, median contract rent may increase home values by less than 1%.

Table 2.11. Robustness check of the housing price in Puerto Rico

	(1) Lvalue	(2) Lvalue	(3) Lvalue	(4) Lvalue	(5) Lvalue	(6) Lvalue
3-bedroom	.31986*				.40537**	.40796**
	(.17974)				(.18134)	(.19088)
4-bedroom	.33408*				.40582**	.45746**
	(.19141)				(.19335)	(.20387)
5-bedroom	.10809				.22087	.2576
	(.22206)				(.22521)	(.23499)
6-bedroom	.26205				.32711	.39277
	(.28309)				(.29074)	(.29798)
7-bedroom	-.17962				-.06174	-.04884
	(.33477)				(.33249)	(.34007)
8-bedroom	-.25482				.01085	.17616
	(.43917)				(.49202)	(.49828)
Net living area (sqft.)	.00017***				.00017***	.00015***
	(.00003)				(.00003)	(.00004)
Bathroom	.3508***				.3025***	.26819***
	(.04074)				(.04113)	(.04243)
Age of House	.00005				.00067	-.00053
	(.00202)				(.00213)	(.00218)
HOA fee ($)	.00178***				.00129***	.00114***
	(.00025)				(.0003)	(.0003)
Parking (#)	.08361***				.07342***	.0724**
	(.02783)				(.02837)	(.02849)
Log of lot size (sqft.)	.07404				.09995**	.09498*
	(.04689)				(.04945)	(.05126)
Ceramic tile floor		-.33965***			-.1365*	-.13403*
		(.10115)			(.07761)	(.07911)
Concrete floor		-1.0001***			-.23219	-.20759
		(.19992)			(.16873)	(.16941)
Terrazzo floor		-.8089***			-.23462*	-.24464*
		(.15566)			(.12076)	(.12716)
Cement roof		-.6772***			-.26201	-.29584
		(.22188)			(.18108)	(.18868)
Concrete roof		-.41869**			-.12708	-.18029
		(.17799)			(.15105)	(.15741)
Slab foundation		.0218			.20136	.17738
		(.15843)			(.12926)	(.12997)
Stem-wall foundation		-.1983			-.0044	-.00515
		(.19328)			(.15655)	(.15839)
Block construction		-.21884			.1148	.1144
		(.18841)			(.16092)	(.16361)
Concrete-block construction		-.24052			.16704	.15898
		(.17588)			(.14449)	(.1474)
Concrete construction		-.10869			.17193	.17546
		(.15574)			(.13066)	(.13264)
Hurricane shutter			.53136**		-.0699	-.02034
			(.22972)		(.16426)	(.16805)
Water View			.56708***		.28648	.33113*
			(.11038)		(.18803)	(.1878)
Has balcony			-.41095***		-.15604**	-.15454**
			(.08349)		(.06875)	(.07045)
Gated community			.80878***		.42123***	.45574***
			(.17159)		(.12595)	(.13018)
Has Pool			.48483*		-.01723	.00981
			(.288)		(.21265)	(.22502)
Has Park			-.68272**		-.35202*	-.53671**
			(.30318)		(.20975)	(.22321)
Has Playground			.07523		.15595	.10492
			(.29293)		(.20394)	(.22321)
Airport distance				-.00002*	-.00002*	-.00001
				(.00001)	(.00001)	(.00001)
Railway distance				0	0	0
				(0)	(0)	(0)
Major road distance				.00001	.00004*	.00004
				(.00003)	(.00002)	(.00002)
Park distance				0	0	0
				(.00001)	(.00001)	(.00001)
Beach distance				-.05706***	-.03032***	-.01682
				(.01129)	(.0102)	(.0112)
Median-HH-income						0
						(0)
Vacant Units						.00028**
						(.00012)
Homeownership rate						-.00593*
						(.00343)
Median Rent						.00051*
						(.0003)

Constant	9.28982***	11.90581***	11.72753***	12.54572***	9.38594***	9.50881***
	(.73887)	(.32833)	(.21631)	(.29131)	(.58569)	(.6403)
Observations	561	665	1001	1001	533	508
R-squared	.62349	.21332	.20511	.13835	.65342	.67111

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Simple OLS model with standard errors in parentheses. Dependent variables column (1) to column (5) are in the log of housing values. X-bedroom is a bedroom dummy with a base of one and two bedrooms. The net living area is the interior minus the total bedroom area in sq-ft. Year and location fixed effects controlled.

2.4.B. Treatment Effect Estimation.

So far, we have established that hurricane buffer distance, flood zone, wind speed, and the left side of the hurricane track significantly impact Puerto Rican home values. However, our goal is to produce a credible outcome that ensures Hurricane Maria substantially affected home value after landfall. The answer to that purpose is a control-treatment estimation.

A 'treatment effect' is the average causal effect of a binary (0–1) variable on a scientific or policy-relevant outcome variable (Angrist, 2010). Following Hurricane Maria in 2017, we believe our policy interest is the presence of hurricane attribute shifts in housing values. Various treatment effect estimation techniques[90] have gained popularity in environmental research, and causal inference has made significant progress. The difference-in-difference (DID) approach is popular in literature. Hence, we ran a treatment effect analysis based on DID and Regression Discontinuity Design (RDD).

2.4.B.1. Buffer Distance Did Treatment Effect.

The yearly house sold data from 2018 to 2021 was available on Zillow's website. As a result, a standard treatment-control analysis based on pre and post-comparison was not possible. Using buffer distance for the DID estimation, we created a 1-mile buffer from the hurricane Maria track. Houses within the "X" mile radius are treated homes, while those outside the "X" mile radius are controlled homes.

[90] Event study, Difference-in-Difference (DID), Regression Discontinuity Design (RDD) etc.

Our treatment effect would be the slope coefficient of the DID estimation. Following the primary hedonic function estimation, each dummy buffer distance variable interacts with the year of the sale in this simple DID technique. The treatment effect is then estimated using the margin command, followed by a predictive plot of the average treatment effect. Table 2.12 shows the treatment effect outcomes.

Table 2.12. Treatment effect of hurricane maria on housing price in standard one-mile buffer distance using conventional Difference-in-Difference method.

Year	**Buffer Distance from Hurricane Maria Tract**					
	1-mile	**2-miles**	**3-miles**	**4-miles**	**5-miles**	**6-miles**
2018	-	-	-	-	-	-
2019	-.0822861	-.0787612	-.0835525	-.4205513	-.2303708	-.2498843
2020	.1999657	.1990049	-.0287441	-.0371627	-.2757068***	-.3683527***
2021	.2263982	-.0336999	-.0971901	-.0869791	-.2143908	-.2512071***
Year	**Buffer Distance from Hurricane Maria Tract**					
	7-miles	**8-miles**	**9-miles**	**10-miles**	**11- miles**	**12-miles**
2018	-	-	-	-	-	-
2019	-.1899159	-.117313	-.2139617	-.0805079	-.0316934	.0876572
2020	-.30162***	-.278489***	-.227723***	-.2467521***	-.2509367***	-.2905015***
2021	.0457155	.0577535	.0721643	-.0450918	-.0421429	-.0718749

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. The treatment effect is the discrete change from the base level outside the buffer and measures the average marginal effect.

Our hurricane Maria buffer distance dummy is generated for up to 12 miles from the hurricane's path. Table 2.12 reveals a couple of interesting findings. For starters, due to a lack of data, there is no treatment effect in 2018. Second, until the 12-mile buffer, the treatment effect for 2019 is negative. Third, in 2020 and within the buffer zone, housing values continue to drop from 3 miles to 12 miles. Fourth, the treatment effect predicts a decline in home values between 2 and 6 miles in 2021. Overall, the DID approach demonstrates that exposure to the hurricane Maria track buffer resulted in a 2-6 mile drop in home values. As a result, the most dynamic range for home value drops in the post-Maria period is 2-6 miles. The appendices show the predicted buffer zone impact in charts A2.2A and A2.2B.

2.4.B.2. Treatment Effect Based on Regression Discontinuity Design (RDD).

Regression Design Discontinuity (RDD) is a relatively new tool for causal inference in environmental research. Thistlethwaite and Campbell (1960) developed RDD. RDD estimates treatment effects in non-experimental circumstances when "assignment" is observable (also known as the "forcing" or "running" variable) (Lee & Lemieux, 2010)[91]. RDD is a quasi-experimental evaluation method in which treatment is assigned based on a continuous eligibility index, a continuous distribution[92] variable. Sharp and fuzzy RDDs are the two types of RDDs. Sharp RDD resembles a traditional DID in appearance. In sharp design, respondents received equal weight to the treatment or control group; in the fuzzy design, some respondents did not get their assigned weight. In randomized experiments, a "fuzzy" technique is similar to no-shows or crossovers like control group members who do receive the treatment (Jacob et al., 2012).

Tables 2.13A and 2.13B used the Stata package 'rdrobust' developed by Calonico et al. (2014) to run the sharp RDD. Table 2.13A shows the results without controlling for the covariate, and we use the same 3-mile buffer distance from Maria Tract. The sharp design generated three RDD methods. Standard RDD considers the treated group on the right side of the cut-off point, which is the opposite of our sharp estimation. The treatment group is on the left side of the cut-off in our analysis.

Table 2.13A shows that home values declined within the 6-mile, 9-mile, and 12-mile buffers from the Maria tract, but there was no expected price dop within the 3-mile

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[91] The RD design is distinguished in the context of an assessment study by a treatment assignment depending on whether an application falls above or below a break on a grading variable, resulting in a discontinuity in the likelihood of treatment delivery at that moment (Jacob et al., 2012).

[92] https://www.betterevaluation.org/en/evaluation-options/regressiondiscontinuity

buffer. The homes within the 9-mile buffers are significant, implying that the value of those homes has decreased because of Hurricane Maria. According to the literature, Hurricane strength at the eye is calm, and the devastation can occur further away from the hurricane's eye. We consider a 6-to-12-mile buffer to be the area where Hurricane Maria wreaked havoc in 2017. The effect is more robust between 6 and 9 miles from the buffer. On the other hand, the cut-off points in figure A2.3A depict a different scenario. For more information, see figure A2.3A in the appendices.

Table 2.13A. Regression Discontinuity Design (RDD) treatment effect based on selective buffer level.

	3-miles Lvalue	6-miles Lvalue	9-miles Lvalue	12-miles Lvalue
Conventional	.59428**	-18.94185	-2.43363***	-.00132
	(.25061)	(14412013)	(.23826)	(.36572)
Bias-corrected	.99051***	-18.88873	-2.09048***	-.1034
	(.25061)	(14412013)	(.23826)	(.36572)
Robust	.99051**	-18.88873	-2.09048***	-.1034
	(.44833)	(14412013)	(.30996)	(.49922)
Observations	1001	1001	1001	1001

**** p<.01, ** p<.05, * p<.1. Standard errors are shown in the parentheses. The regression results are estimated using Stata Package "rdrobust." No covariate control.*

In our analysis, we controlled for covariates in Table 2.13B. Once we considered the effects of Hurricane Maria, our findings suggest that houses within a 3-mile radius experience a significant price drop due to hurricane exposure. However, the house price increased within the 6-mile buffer again, fell within the 9-mile buffer, and increased within the 12-mile buffer criteria. Some covariate variables had a more significant impact on determining the home value.

This outcome is the contrasting result we got when we removed covariates. We checked the cut-off figure A2.3B for any significant changes because of these changes in the sign. Appendix figure A2.3B supported or analysis's conclusion. This covariate-controlled analysis does not reveal the net result of the price drop zone. We extended our RDD analysis in the following subsection regarding homes on the left side of Hurricane Maria's track.

Table 2.13B. Regression Discontinuity Design (RDD) treatment effect based on selective buffer level

	3-miles Lvalue	6-miles Lvalue	9-miles Lvalue	12-miles Lvalue
Conventional	-.60247**	1.0908*	-.18826	.63636***
	(.26686)	(.6062)	(.1492)	(.22278)
Bias-corrected	-.90224***	1.08519*	-.2897*	.74178***
	(.26686)	(.6062)	(.1492)	(.22278)
Robust	-.90224**	1.08519	-.2897*	.74178***
	(.42884)	(.88579)	(.17036)	(.27229)
Observations	561	561	561	561

***** p<.01, ** p<.05, * p<.1*. *Standard errors are shown in parentheses. This estimation controlled the covariates. The regression results are estimated using Stata Package "Rdrobust."*

2.4.B.3. Determination Of Treatment Buffer Based on Left Side Home Specification.

The previous subsection, which employed the traditional DID and sharp RDD techniques, failed to produce a conclusive price reduction buffer due to Hurricane Maria. As a result, we'll have to take a different approach to the lensing. As a result, the RDD estimation in Table 2.14 now includes the left side hurricane track dummy. We used a fuzzy RDD estimation technique instead of a sharp RDD. Because homes on either side of the cut-off point might be exposed to the same level of hurricane shock. Hurricane Maria may have caused devastation to some controlled homes outside and closer to the cutoff.

Table 2.14. Regression Discontinuity Design (RDD) treatment effect is based on the house location (left side) relative to the Hurricane Maria Tract.

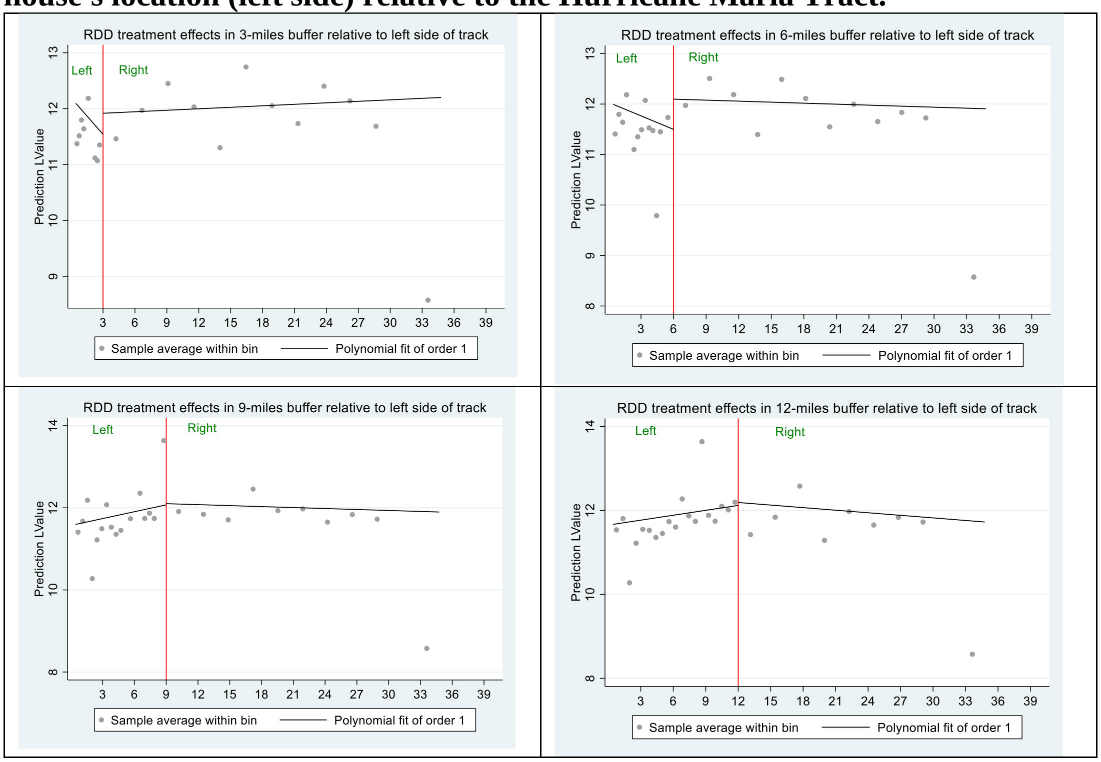
	(3-miles buffer) Lvalue	(6-miles buffer) Lvalue	(9-miles buffer) Lvalue	(12-miles buffer) Lvalue
Conventional	-.66194**	-40.4078	-.38598	-4.48803
	(.26604)	(63.45143)	(.27641)	(8.91032)
Bias-corrected	-.07997	-38.88865	-.35632	-5.29078
	(.26604)	(63.45143)	(.27641)	(8.91032)

Robust	-.07997	-38.88865	-.35632	-5.29078
	(.52608)	(65.98013)	(.29783)	(11.11394)
Observations	561	561	561	561

**** p<.01, ** p<.05, * p<.1. Standard errors are shown in parentheses. This estimation controlled for covariates. The regression results are estimated using Stata Package "Rdrobust."*

We can now see an improvement in the outcomes. Following Hurricane Maria, home values dropped within the 3- and 6-mile buffer. From figure 2.3, we reached the same conclusion. Although the nine and twelve miles produced a negative coefficient, the RDD graph shows a price increase; the results are far from convincing. As a result, our effective price reduction buffer zone within the hurricane track is 3 to 6 miles, confirming the same findings from the DID method.

Figure 2.3: Regression Discontinuity Design (RDD) treatment effect based on the house's location (left side) relative to the Hurricane Maria Tract.



2.4.B.4. DID And RDD Buffer Robustness Check.

According to the DID and RDD models, the effective buffer zone is 3 to 6 miles. The value of a home in the buffer zone will depreciate due to Hurricane Maria's passing through. We ran a separate Stata package called "cmogram" as a robustness check on those findings, and it produced a similar outcome of treatment effects. Table 2.15 shows the results with a one-mile and three-mile buffer between them.

Table 2.15. General to specific treatment effect estimates concerning the distance buffer.

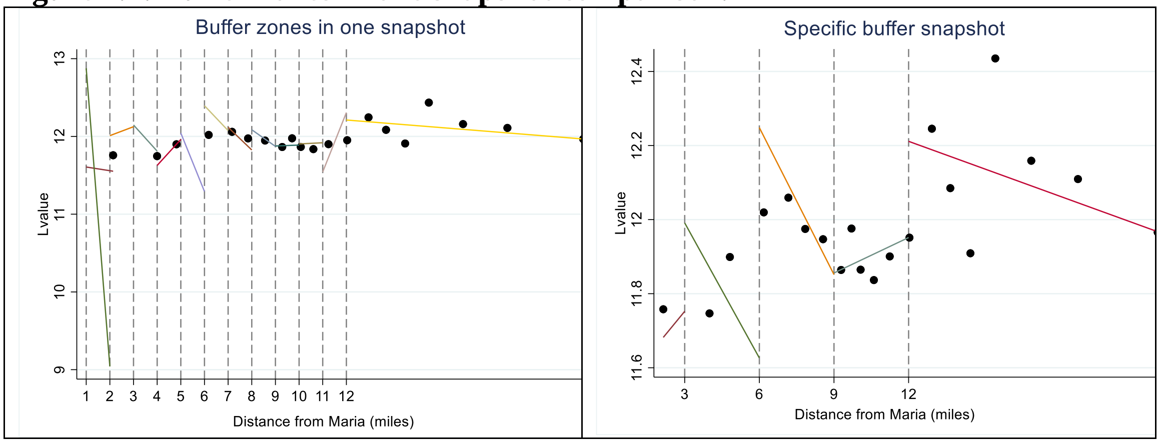
General Model Estimation Results													
	D≤1	**1≤D≤2**	**2≤D≤3**	**3≤D≤4**	**4≤D≤5**	**5≤D≤6**	**6≤D≤7**	**7≤D≤8**	**8≤D≤9**	**9≤D≤10**	**10≤D≤11**	**11≤D≤12**	**D≥12**
Intercept^{A}	11.65	16.71	11.78	11.15	10.29	15.80	14.31	14.15	13.79	11.76	11.75	3.13	12.50
Slope^{A}	-.0472	-3.835	.1148	-.3365	.3339	-.752	-.3203	-.2916	-.2133	.0121	.01481**	.7639	-.0243
Specific Model Estimation Results													
			3≤D			**3≤D≤6**			**6≤D≤9**			**9≤D≤12**	**D≥12**
Intercept^{B}			11.50			12.35			13.04			11.56	12.50
Slope^{B}			.081762			-.121			-.132*			.031	-.024

***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively. Letter' D' stands for distance from Maria tract in miles. Superscript 'A' denotes the general model estimation, and 'B' stands for the reduced buffer. Slope measures the treatment of Hurricane Maria on the housing value.

Within the two-mile buffer, the slope coefficient (treatment value) shows signs of home value decline in the one-mile buffer general model estimation. Even so, because the slope is higher, the trend is offset between 2≤D≤3 miles buffer. As a result, the D≤3 slope of the treatment effect is positive and upward sloping in specific treatment estimation. Figure 2.4's visuals support the same conclusions.

Again, the treatment effect of 3 to 5 miles between 3≤D≤6 buffer zones cancel out, whereas there is a significant negative slope coefficient of treatment between 5- and 6-mile buffer zones. As a result, figure 2.4 presentation confirms that home values within a 3- to 6-mile buffer predicted a drop following Hurricane Maria. As a result, it demonstrates the previous findings that the hurricane effect is more significant for Puerto Rican homes within 3-6 miles of the buffer.

Figure 2.4: Buffer zones in one snapshot comparison.



2.5 Discussion and Policy Implication:

The second chapter sheds light on Hurricane Maria's effect on Puerto Rico's home values. We investigated the housing market from the demand side perspective. Our finding revealed that housing value depreciation was dominant in the 3-6 miles from the Hurricane Maria track. Furthermore, ground-floor and top-floor homes were more vulnerable to Hurricane Maria exposure. But there are some limitations that should be noted in explaining our findings.

The Island inherited a massive debt of $74 billion[93] due to the declining manufacturing sector and job losses in the aftermath of the great recession in 2009. In 2016 the US House of Representatives passed a bill called Puerto Rico Oversight, Management, and Economic Stability Act (PROMESA[94]) to restructure the debt. President Obama signed the bill in 2016 and made it a law.

[93] https://peoplesdispatch.org/2021/10/20/puerto-ricans-resist-austerity-measures-and-corporate-corruption/

[94] https://oversightboard.pr.gov/about-us/

The PROMESA board enacted a stringent[95] austerity policy, cutting social security pensions, funding for the University of Puerto Rico, Public schooling, and hospitals. This austerity policy highlighted that residents were exempted from federal, state, and municipal taxes. Moreover, the creditors were barred from exercising collection activities until 2017 from household debts (Dolan, 2018). As a result, the household had some additional savings to mitigate adverse shocks arising from previous natural disaster experiences. These extra savings could give them more bargaining power in home purchase decisions. Our paper did not account for the effect of these austerity policies in Puerto Rico. Hence, from the political and economic point of view, these exemptions of tax could potentially benefit homebuyers which were not reflected in our paper. We intend to extend this notion of austerity effect in our subsequent investigation.

Another limitation of our paper was that we ran more than three interaction terms in our analysis. Our objective was to find the combined effect of different hurricane-related information. But accordingly to Steyerberg (2009), adding more than two interaction terms may reduce the significance of results. Hence, we plan to include some additional models to address this concern in our extended analysis.

The main contribution of this chapter is to provide a systematic understanding of what factors contributed to the declining price in Puerto Rico's housing market following Hurricane Maria. On the contrary, we did not control for property level heterogeneity because, within the same structure, exposure to the same hurricane level does not affect a house of a similar nature. House A vs. House B could be subjected to different building codes and permits. Their structural resilience may not be the same either. We intend to visit

[95] https://unctad.org/system/files/non-official-document/YSI_Merling.pdf

the role of structural characteristics based on wind or flood engineering models. We believe integrating those model outputs into our estimation and controlling for the structural factors can enrich our analyses.

Apart from these limitations, we think our findings would help guide planners and policymakers in designing and implementing hurricane-resilient building codes in Puerto Rico. Such policy change could minimize the impacts of natural disasters on future property values.

2.6 Conclusion:

This paper proposes a novel path for analyzing the housing market in Puerto Rico, particularly given the island's vulnerability to hurricanes like Maria. We demonstrated that home values depreciated in the aftermath of Hurricane Maria. Our paper is the first empirical study of the housing market in Puerto Rico to document this trend. Three significant findings are worth mentioning in this paper.

First, we discovered an effective hurricane buffer zone between 3 and 6 miles from Hurricane Maria's projected path, which could significantly lower housing values. Second, hurricanes passing through a flood zone depress home prices in Puerto Rico even more. In Puerto Rico, houses on the second level or above are more vulnerable to hurricane damage.

One of the major limitations of our paper is that we could not compare home values before and after Hurricane Maria's landfall. Access to home sales data before Hurricane Maria could have opened more possibilities for analyzing the impact of a hurricane on the Puerto Rican real estate market. Another limitation in this paper is that we could not obtain the complete list of home values sold following Hurricane Maria. Our analysis could have improved if we had a larger sample size. Finally, this study provides evidence that Hurricane Maria had a significant dent in the Puerto Rican housing market.

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Appendix.

Figure A2.1. Checking normality.

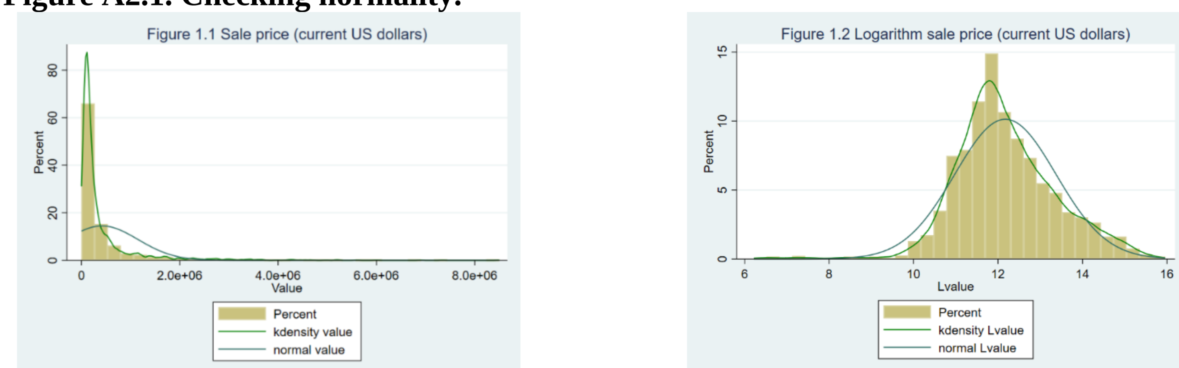
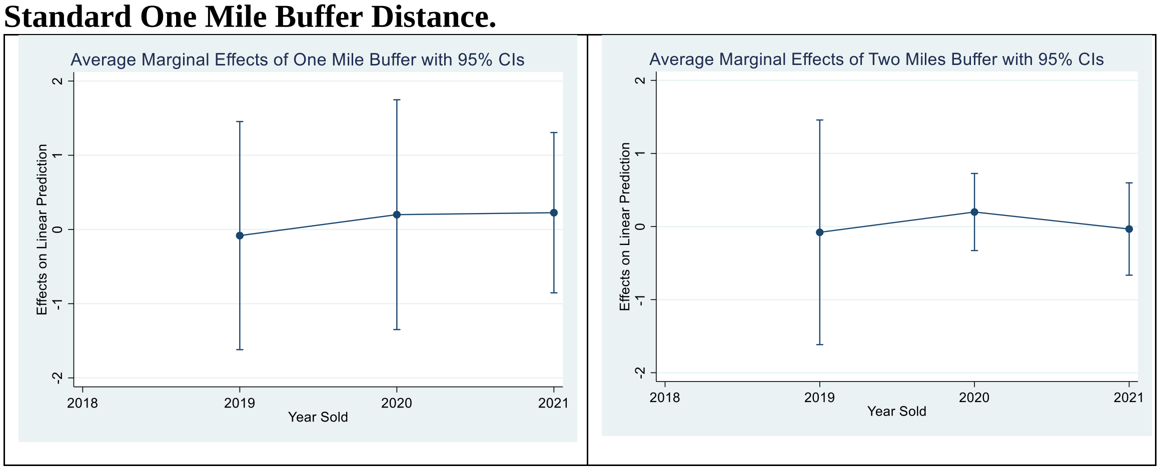


Figure A2.2A. Simple DID Treatment effect of Hurricane Maria on Housing Price in Standard One Mile Buffer Distance.



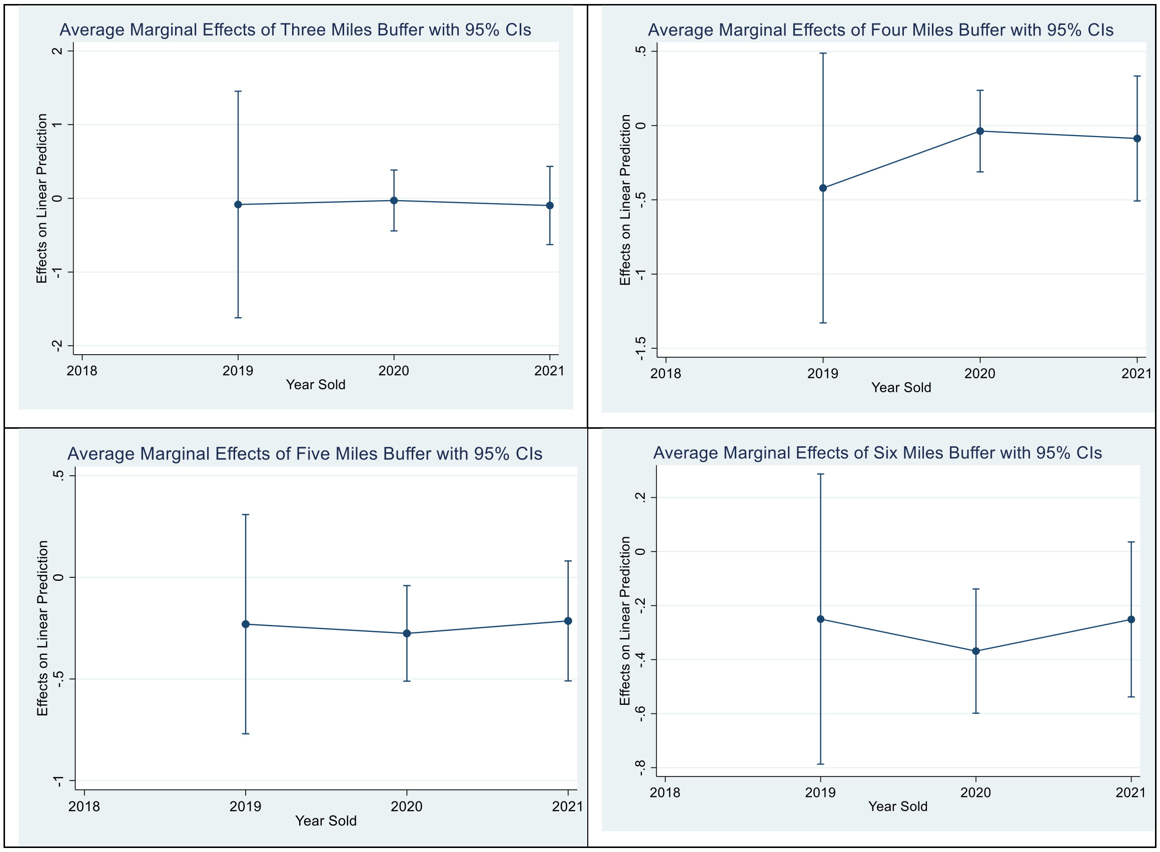
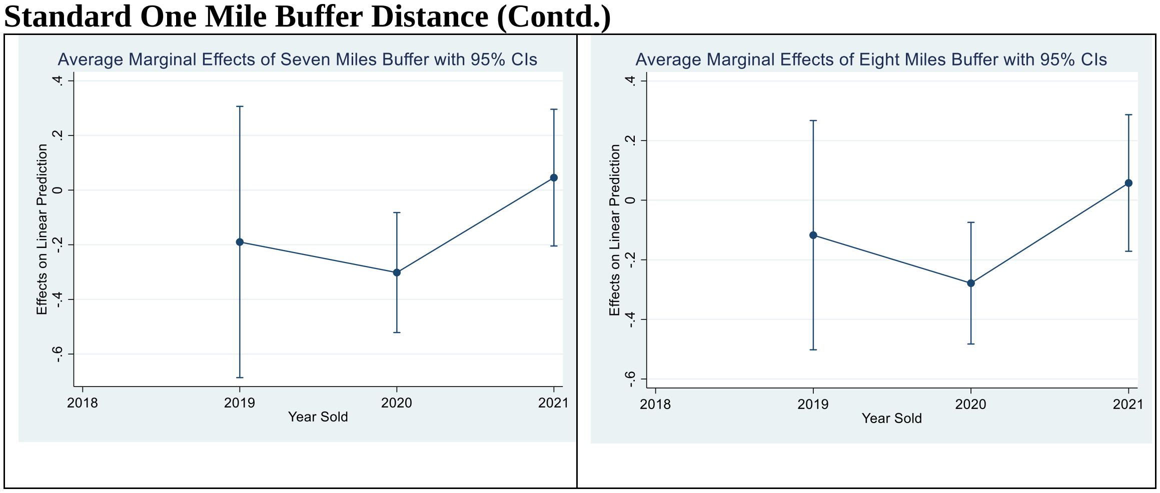


Figure A2.2B. Simple DID Treatment effect of Hurricane Maria on Housing Price in Standard One Mile Buffer Distance (Contd.)



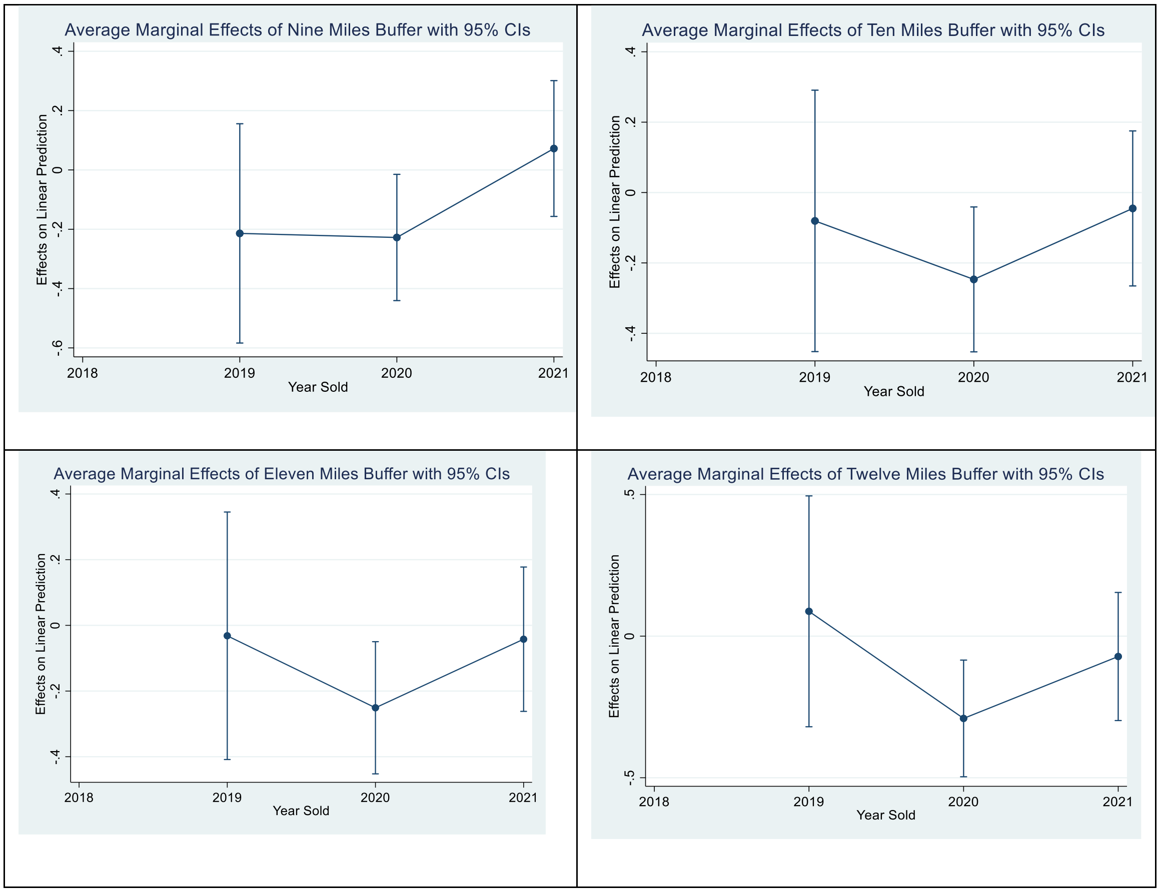
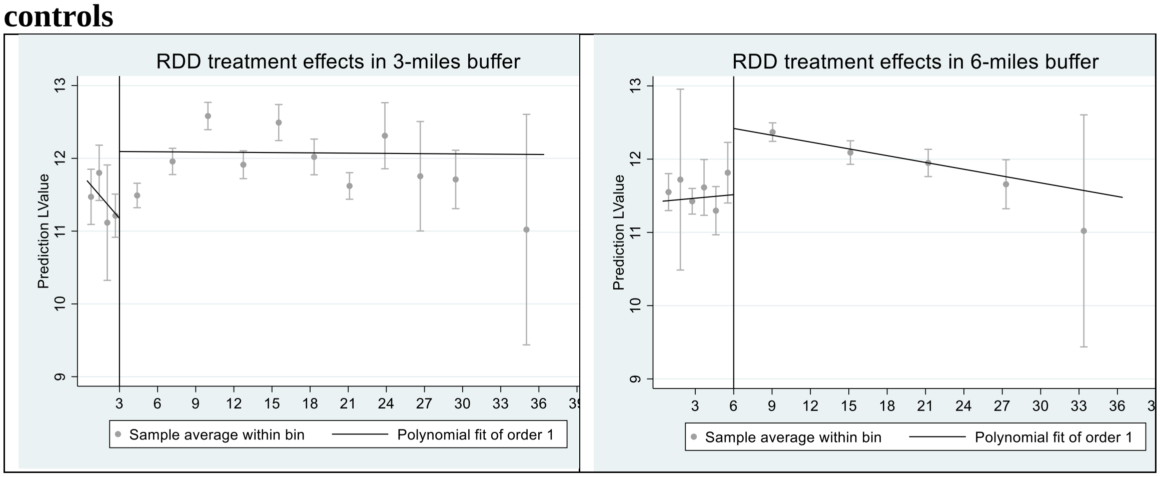


Figure A2.3A: Regression Discontinuity Design (RDD) treatment effect without controls



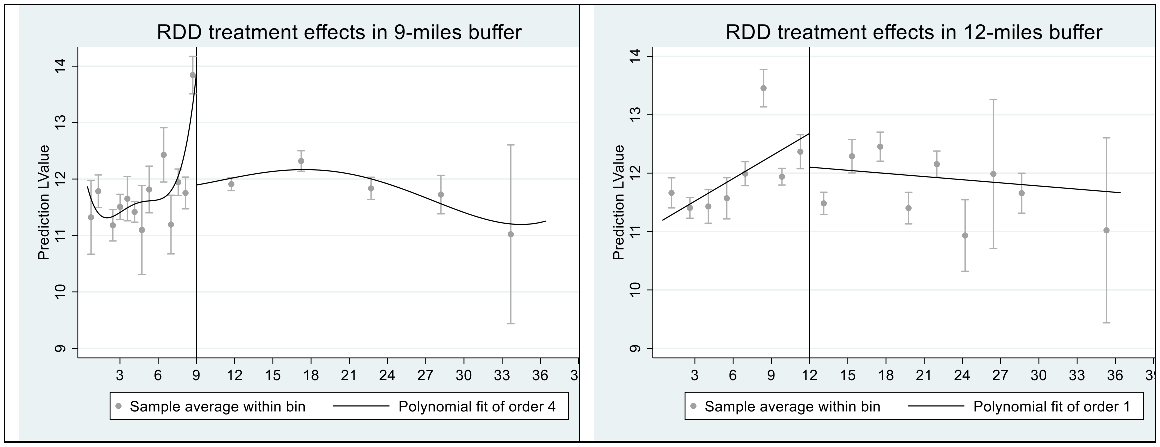
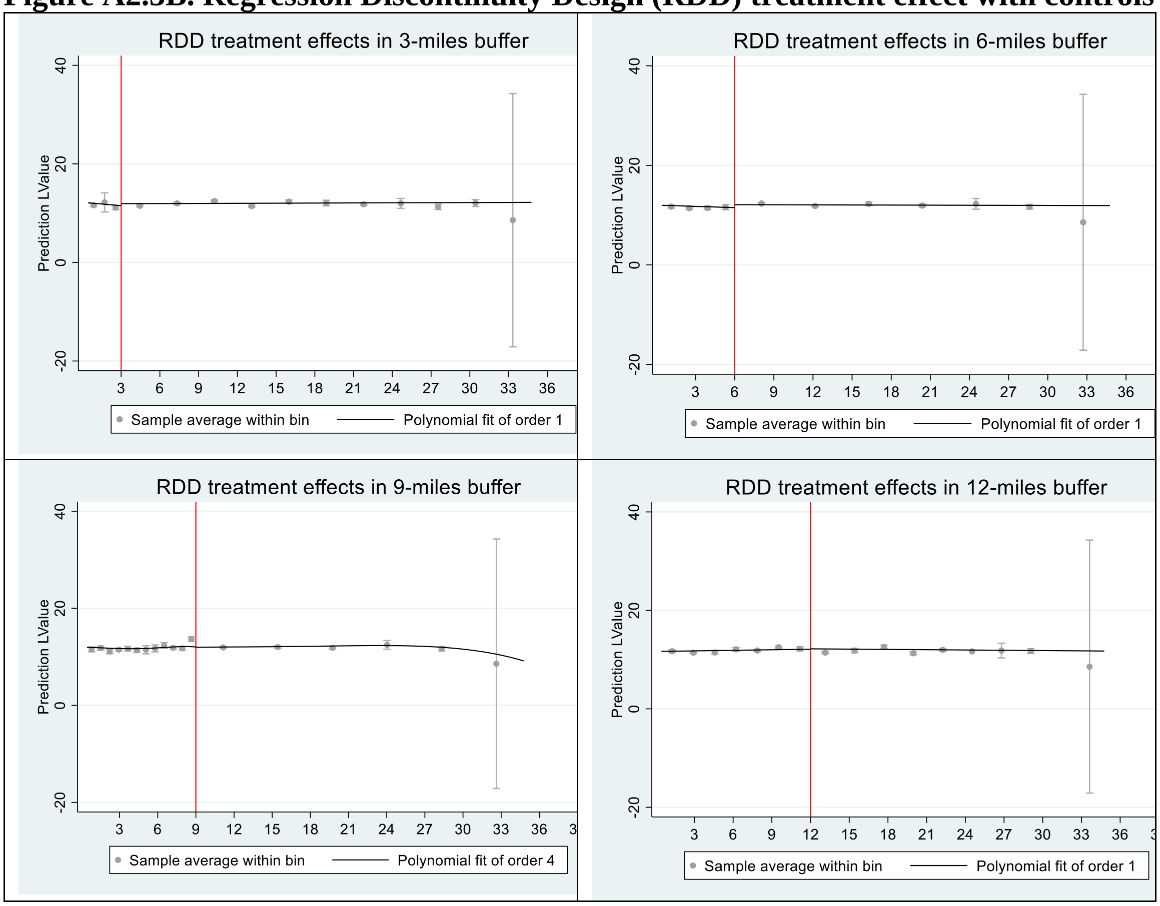


Figure A2.3B. Regression Discontinuity Design (RDD) treatment effect with controls



Chapter 3

Hurricane and Performance of Critical Utility Infrastructures: Analysis with Inoperability-based Input-Output Modeling

3.1 Introduction:

The Presidential Policy Directive (PPD) on “Critical Infrastructure[96] Security and Resilience” promotes national unity to improve and sustain functional, secure, and resilient crucial infrastructure (Directive, 2013). Because an operational infrastructure is critical to the economy's smooth operation, it impacts the state of economic activity and the type of activities or sectors that may flourish inside a country[97].

Critical infrastructures are interdependent. Their connections may be physical, functional, economic, geographic, or logical (Santos et al., n.d.). For example, electricity failure for a few days hampers the production and distribution of goods or services dependent on it. Such shortcomings, commonly known as inoperability, can reduce the functionality of critical infrastructure such as electricity, water, transportation, telecom, Internet, workplace, grocery, etc. Thus the impacts of one infrastructure failure may spread across infrastructure systems, resulting in cascading and increasing failures that might exacerbate a crisis (Lewis & Petit, 2019).

This paper uses Hurricane Harvey to understand the effect of critical infrastructure systems and their interdependences in the aftershock of a natural disaster. Hurricane Harvey is the second most damaging hurricane in US history. On August 25, 2017, Harvey

[96] There are 16 critical infrastructures as per Presidential Directive 21 and supersedes Homeland Security Directive 7.

[97] Part of this importance is stemmed from https://www.publicsafety.gc.ca/cnt/rsrcs/pblctns/2016-rl-crtclnfrstrctr-ntnlprsprty/index-en.aspx

made landfall as a category four strength hurricane in the coastal areas of Texas. Approximately 20,000 homes were demolished, and more than 300,000 homes were without power for days. The Harvey alone cost $125 billion in damage to the State of Texas. In Houston alone, the highway damage was around $200 million, and the retail trade loss was approximately $1 billion. Houston is situated on plain land and is known for its susceptibility to flooding. The residents of Houston did not evacuate[98] during the Harvey landfall and faced dire consequences of the home locked due to the flooding. Some had no water, electricity, or gas connections for days. Hence, assessing the effect of Harvey on Houston's critical infrastructure and utility service perturbation gives rise to an urgent concern for the well-being of the affected families.

Following a natural disaster inoperability of the critical infrastructures causes significant economic losses to interdependent sectors (Akhtar & Santos, 2013b; Haimes & Jiang, 2001; Rose et al., 1997; J. R. Santos & Haimes, 2004). Assessment of such disaster-led inoperability is not easy. There is a risk associated with it, especially in collecting reliable data and features related to the disaster. As a result, researchers preferred Computable General Equilibrium (CGE) modeling or another computational method to investigate such inoperability in the past. The challenge arises when authorities want to know the extent and length of a major infrastructure disruption and its effect on impacted populations (J. Santos et al., n.d.).

We were fortunate that we did not have to deal with data availability. In 2020, Florida International University's ORDER-CRISP project, which the National Science Foundation (NSF) funded, conducted a household survey on Hurricane Harvey-affected

[98] Numerous public media sources (NPR, CNN, Washington Post) confirmed that Houston Mayor did not issue an evacuation order.

households. A module in that survey records the utility outages that respondents have experienced and their duration. We entered that information into the inoperability input-output model as hurricane features to track the impact on economic loss in the aftermath of the disaster. As a result, this paper aims to estimate the cascading effects (losses) of interdependent economic sectors after Hurricane Harvey's landfall in Houston, Texas. To account for the combined inoperability of the interconnected sectors, we used Santos & Haimes's (2004) Dynamic Inoperability Input-Output Model (DIIM) for estimation.

The ORDER-CRISP project generated a Graphical User Interface (GUI) based DIIM methodology. The household survey had 13 utility disruption questions, but we used transportation, electricity, water, telecommunication, Internet, workplace, and grocery disruption for our analysis. The GUI estimation module produced the output of ten sectors with the most inoperability and ten industries with the most economic damage. We ran individual DIIM estimation scenarios as well as the combined inoperability.

Our findings show that household disruption at work caused the most economic loss ($3.8 billion) in Houston, but the integrated sector loss is estimated to be around $4.1 billion. As a result, workplace disruption in Houston attributed to the lion's share of the economic loss.

The rest of this article is structured as follows. Section 3.2 explores the Socioeconomic impacts of utility disruptions and methods used for analyzing them, followed by Harvey-led utility disruptions and the significance of studying their effects in section 3.3. Section 3.4 describes the data and methodology. We present our empirical results in section 3.5. In section 3.6, we show the discussion and policy implications. Section 3.7 concludes the paper, accompanied by a bibliography.

3.2 Socioeconomic Impacts of Utility Disruptions and Methods Used for Analyzing:

Infrastructure systems offer essential services such as electricity, water, transportation, sanitation, and communication for social and economic activity (S. E. Chang, 2016). Damage to this system means essential services will be unavailable during a natural disaster. Reduced disruptions and improved local resilience are two effective ways to combat this. In the literature, various modeling techniques were used to estimate the impact of such utility disruptions. These utility disruptions could be estimated on a local, regional, state, or national scale.

For example, Rose et al. (1997) calculated the regional impact of a power outage caused by an earthquake near Memphis, Tennessee. The author's findings suggested that reallocating electricity across sectors with limited transmission could shorten the recovery time and boost GDP by up to 7%. Again, based on a respondents' evacuation plan, Halim et al. (2021) calculated the hurricane-induced disruption in Hurricane Sandy-affected areas. According to the researcher’s conclusions, people with power outages and financial losses were the most likely to evacuate during Hurricane Sandy.

On the other hand, Balakrishnan & Zhang (2018) used Agent-based modeling to rank the disaster-affected regions in Austin, Texas, based on the extent of impact disruption. The author's research aimed to create a priority index. This priority index would assist local officials and utility service providers in identifying areas that require immediate attention and support. Hurricane Wilma wreaked havoc on Florida, particularly in South Florida. So, Chatterjee & Mozumder (2015) evaluated the impact of Hurricane Wilma on utility outages and residents' well-being in South Florida. Their research showed that household well-being decreased when Hurricane Wilma cut off electricity and water services. Authors argued that significant investment is required to minimize disruption and improve residents' well-being.

Rose et al. (2011) used Computable General Equilibrium modeling (CGE) to investigate the Los Angeles earthquake-induced water supply disruption. The author's central concept was adaptive resilience, which explains how people can stay in service for long periods during a crisis. In their study, the authors distinguished between disruptions at the macroeconomic, microeconomic (firm, household), and mesoeconomic (different economic sectors) levels. According to the Rose et al. (2011) study, the Los Angeles water disruption cost the city several billions of dollars due to the earthquake Verdugo and the resulting business sector disruption. Rose & Liao (2005) used CGE modeling to investigate sectoral and local economic effects on the Portland Metropolitan Water System following a major earthquake. They studied supply-side disruptions, establishing a link between individual businesses and macroeconomic resilience, as well as producer adaptation to the interruption.

New Jersey residents' ability to recover from a hurricane depends heavily on the extent of utility outages they experience. Meng & Mozumder (2021) used two-stage household data from Hurricane Sandy to show that long periods of turmoil result in significant monetary losses. Those who had been through a hurricane and had a higher level of education were more resilient during hurricane Sandy. The partial consideration of the macroeconomic impact of utility disruption may differ from that of the general equilibrium context. Rose et al. (2005) used this concept to investigate the Los Angeles electricity blackout. In a partial equilibrium analysis, the authors claimed that different types of coping or resilience, such as conservation, backup generators, and rescheduling of production, could reduce the economic effects of the power outage by 90%.

In the literature, simulation analysis of utility disruption is standard; for example, Larsen et al. (2018) predicted the long-run costs of electricity disruption to customers in the United States under various severe environmental scenarios. Their findings revealed that these issues could result in a loss of $1.5-$3.4 trillion in the middle of the United States. Similar studies (Küfeoğlu, 2015; Rose & Guha, 2004) looked at the impact of electric outages on the economy.

Water, electricity, business closures, and other utility disruptions are the focal point of the utility disruption research. A natural disaster could disrupt the highway network, causing both ground and truck transportation disruption. Shi et al. (2015) studied the impact of the 2008 Wenchuan earthquake in China's Sichuan province on the highway network. Regional businesses felt the indirect influence of the highway closure. Hence, the authors created a CGE model to estimate the impact of the business interruption. And the study found that without a resilience factor, Sichuan province had an estimated loss of around CNY 1.08 billion. A local resiliency factor could reduce the economic loss by 88 percent to CNY[99] 1.08 billion.

In 2003, three major earthquakes struck northeast Japan. The massive impact of those earthquakes had a significant effect on the utility sector, affecting 66 hospitals in the area. Achour et al. (2014) used a pluralistic and quantitative approach based on a computer-generated discriminant function analysis approach to estimate the cost of three earthquakes in local hospitals. According to their findings, infrastructure vulnerability is the main

[99] CNY is Chinese Yuan.

challenge of such disturbance. As a result, the hospital was forced to provide a subpar level of healthcare to the local community and could not maintain its usual level of care.

Wing & Rose (2020) evaluated the prolonged power outage in the California Bay Area using a two-sector model. The researchers then compared the CGE result to the traditional willingness to pay model to calculate the welfare loss caused by both approaches. According to their findings, the CGE model's estimated welfare loss is much smaller than the willingness to pay method. Their main conclusion was that a local economy could lessen the economic effects of power dimout through resilience and mitigation. Similarly, Bhattacharyya et al. (2021) calculated the financial losses caused by weather-related power outages in the United States from 1997 to 2019. They calculated a total loss of $11.6 billion using an inoperable IO model, assuming 1% inoperability. Furthermore, their research identified the most vulnerable industries due to the utility sector's inefficiency.

Mitsova et al. (2018) compared the power outage disruption caused by Hurricane Irma in Florida between urban and rural counties. The authors also calculated the outage length based on different wind exposures. According to their calculations, the peak outage occurred in rural areas during Hurricane Irma, affecting primarily socioeconomically vulnerable groups.

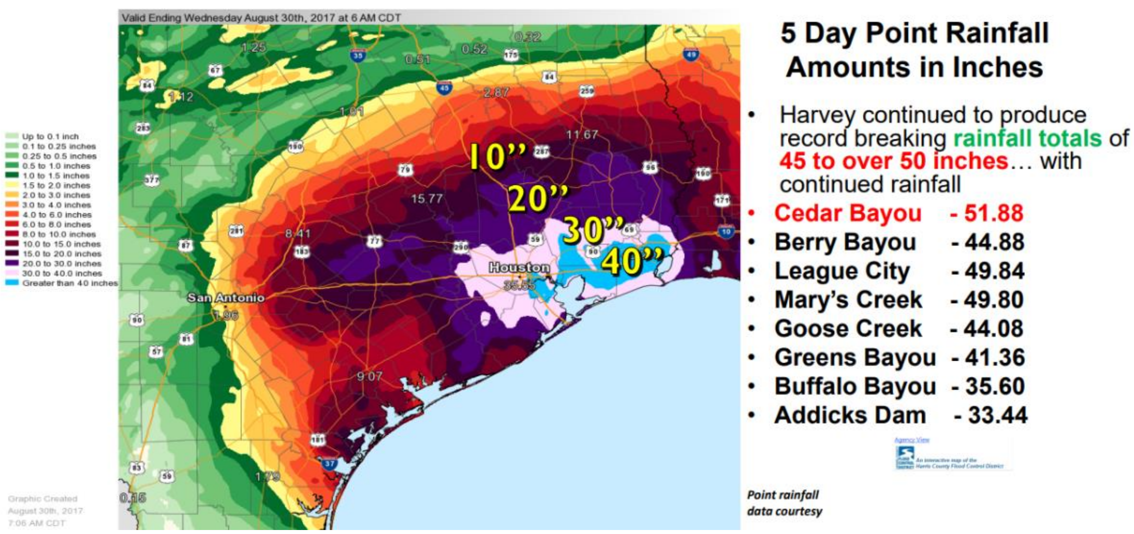
3.3 Harvey Led Utility Disruptions and The Significance of Analyzing Its Impacts:

On August 25, 2017, Hurricane Harvey, a category four storm, hit the Texas coast[100]. It was the first hurricane to hit the Texas coast since 1990. Flooding wreaked

[100] https://www.weather.gov/hgx/hurricaneharvey

havoc, killing[101] at least 100 people. The Houston Metropolitan Statistical Area (MSA) received the brunt of the damage. According to a health report released by the Houston Department of Health, "*However, instead of continuing inland as most hurricanes do, with a gradual loss of strength and destruction, Harvey stalled over the south and southeast Texas for days, slowly meandering along the coastal area. The winds decreased, and Harvey became a tropical storm, but the rains increased. The storm caused heavy rainfall and flash flooding, especially over the eastern portions of the area, including Houston*[102]". In the first five days after Harvey made landfall, Figure 3.1 depicts the extent of heavy rain in rivers and swampland.

Figure 3.1: Five Day Rainfall Totals within Rivers & Swamplands



Source: https://www.weather.gov/hgx/hurricaneharvey

[101] The information is retrieved from https://en.wikipedia.org/wiki/Hurricane_Harvey

[102] The entire report can be found at https://www.houstontx.gov/health/reports/documents/hurricane-harvey-report-hhd-response-2017.pdf

The damage of Hurricane Harvey was approximately $125 billion[103], which is second to Hurricane Catrina. Furthermore, Harvey destroyed 200,000 homes, 0.75 million people registered for FEMA assistance, and 10,000 were rescued by federal forces while trapped in their homes due to the flood (Amadeo, 2018). The electric company ERCOT is the leading power supplier in the greater Houston area[104]. The chronicle of ERCOT[105] on Hurricane Harvey reported that more than 70,000 customers were without power on August 25, more than 211,000 on the morning of August 26, and more than 300,000 customers were without electricity by noon. Their final update on September 6 stated, "*While power restoration efforts will continue for an extended period in some areas, the number of impacted transmission facilities and generation resources has decreased considerably since Hurricane Harvey hit the Texas Gulf Coast on August 25*".

We were concerned that some customers still had no access to power even after two weeks after Harvey's landfall. Electricity transmission is vital because critical utility production depends on it. The cascading impact of these two weeks of no electricity on the overall economic activities is unthinkable. This notion of disruption would lead to a potential loss of GDP in Texas, thereby in the Houston area.

With inhabitants of 2.4 million, Houston is the most populous city in Texas, and its area of 637.4 square miles makes it the largest city in the United States by total area[106]. In

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103 UpdatedCostliest.pdf (noaa.gov)

104 The ERCOT region includes Houston, and its vicinal counties.

105 https://www.ercot.com/help/harvey

106 The information is sourced from the Wikipedia.

addition to meeting its own needs, Houston supplies water to three surrounding counties. According to the municipal website, Houston can offer over 1.2 billion gallons of guaranteed surface water per day and more than 200 million gallons per day (MGD) of viable groundwater resources until 2050. The sustainable aquifer and Lake Livingston are the sources of this water. In 2017, the city's drinking water operation[107] produced and distributed more than 160 billion gallons of water over 7,000-mile-long pipes, according to the city's website. Following Hurricane Harvey, a large population faced unknown contamination in their water supply.

The submerged water sources during Hurricane Harvey's flooding explains water contamination. According to a report published by the Texas Tribune[108]," *Gov. Greg Abbott announced that the US Environmental Protection Agency had completed site assessments at all 43 Superfund sites in areas affected by the storm. He said in a press release that two of those sites — the San Jacinto Waste Pits and the US Oil Recovery — will require further assessment, which will take several days to complete*". As a result, the submerged superfund sites added a layer of inoperability to Houston's water supply and the water service disruption. Analyzing the economic impact of such a prolonged water outage in Houston will help determine the interdependent sector's financial loss.

The modern transportation system transports goods and services from point A to point B as part of the supply chain. A good highway can guide economic development and growth. Soon after Hurricane Harvey's landfall, Houston's transportation system collapsed.

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[107] https://www.publicworkplaces.houstontx.gov/drinking-water-operations

[108] https://www.texastribune.org/2017/09/08/post-harvey-houston-extent-water-contamination-unknown/

Over a million cars[109] were wrecked in Huston during Harvey's landfall, according to a wired.com news release. In a separate Houston newspaper[110] article, Houston's Transit Agency recorded the damages incurred by the city's public transportation system. Following Harvey, the Metro hopes to recoup some of the losses it suffered due to the historic floods. Finally, according to the online newspaper Chron[111], the Texas Department of Transportation (TXDOT) estimated $185 million in costs from August 25 to September 1 due to the hurricane's arrival and thumping rains[112]. Understanding the extent of the economic damage caused by Harvey in the greater Houston area requires determining the size of the transportation-dependent sector's monetary loss.

We will now turn our attention to Harvey's effects on the workplace. People were unable to get to work due to the stagnant flooding. As a result, many affected people were declared unemployed for days after Hurricane Harvey. According to an online news

[109] https://www.wired.com/story/harvey-houston-cars-ruined/

[110] https://www.houstonpublicmedia.org/articles/news/2017/09/08/236253/houstons-transit-agency-tallies-up-damages-after-harvey/

[111] https://www.chron.com/business/article/Harvey-damage-nets-Texas-nearly-30M-in-federal-12957521.php

[112] https://www.chron.com/business/article/Harvey-damage-nets-Texas-nearly-30M-in-federal-12957521.php

website[113], the Texas Workplace Commission received 125,000 applications for unemployment benefits[114].

Texas was without cable television, internet, and phone service for several days. Because according to mysanantonio.com[115], Hurricane Harvey destroyed 364 cell towers and roughly 200,000 homes in Texas. Their findings revealed the most severe consequences in Harris County, Houston, and Nueces County, including Corpus Christi. Hence, the internet and telecommunication industry are crucial to modern society. A disruption in the telecom sector leads to the malfunction of industries reliant on it.

Finally, many grocery stores could not resume normal operations due to the prolonged floodwaters. As a result, people form lines to buy the groceries they want. According to Supermarketnews.com[116] 's investigation, "*The weather intelligence firm Planalytics said Monday it already estimates Harvey has cost Texas retailers more than $1 billion in lost sales. It said Harvey would likely be among the top five or 10 most expensive disasters in history for retailers and rival the economic devastation brought by the last Category 4 hurricane to make US landfall, Hurricane Charley, in 2004, which had a $15 billion impact*".

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113 https://www.houstonpublicmedia.org/articles/news/2017/09/15/237473/125000-unemployed-texas-workplaceers-have-filed-claims-after-harvey/

114 https://www.houstonpublicmedia.org/articles/news/2017/09/15/237473/125000-unemployed-texas-workplaceers-have-filed-claims-after-harvey/

115 https://www.mysanantonio.com/business/technology/article/Hurricane-Harvey-leaves-Texans-without-internet-12069233.php

116 https://www.supermarketnews.com/news/houston-stores-facing-flood-devastation

According to a new source (exclusive.multibriefs.com), the big grocery chain used a helicopter to transport workers and supplies, causing grief and misery for small grocery owners. According to mybrief.com, "*One can only imagine how much harder it has been for the smaller, local grocery stores. As the waters receded and people filtered back to the stores, the store owners were the first to witness shock and heartbreak. Along with flooding, they also dealt with additional issues like power outages and staff shortages. The latter resulted from hundreds stranded without the means of travel or rescue across the impacted zones*." The goal of our research is clear, based on all these subsequent utility outages and the resulting economic loss. To answer our research question, we need to examine the impact of these disruptions on various sectors and the consequential economic loss.

3.4 Data and Method:

We think household survey data-based DIIM analysis is one of the superior methods for analyzing utility disruption. The secondary data source makes it impossible to track households that lost power because of a recent natural disaster. Household features and service demands vary, making them less prone to service interruptions because household exposure to service outages influences the societal implications of infrastructure service disruptions (Esmalian et al., 2021).

As a result, using the input-output model to assess infrastructure disruption necessitates a thorough review of previous research. As a result, many studies employed household survey methodologies to collect data on the impact of disasters on people's daily lives and the disaster preparations they make. For example, the Computable General Equilibrium (CGE) Model or the Input-Output (IO) Model can be used to assess critical infrastructure disruption caused by natural disasters. However, IO outcomes frequently overestimate[117] the impact of a disaster because IO outcomes vary considerably due to different economic mechanisms (Cimellaro et al., 2019). CGE, on the other hand, tends to underestimate[118] the effects of natural disasters (Rose, 2004). If the data from the Household Survey is collected efficiently, we can avoid these problems.

The study data came from a survey conducted in Texas two years after Hurricane Harvey made landfall. As part of a National Science Foundation-sponsored research project (ORDER-CRISP), investigators at the Florida International University constructed a survey to examine the socio-economic impacts of utility and community service interruptions on individual families' recovery and wellbeing. The survey was conducted over two weeks in September 2020 by Qualtrics XM, a well-known market research firm.

Qualtrics[119] used a 28-question Qualtrics ESOMAR[120] survey with a detailed explanation of the online sampling procedures. As a result, as research methodologies advanced in the ESOMAR, Qualtrics did not use single panels. Qualtrics used convenience sampling from various sources to create diverse, representative data sets. Recruitment methods include websites, member recommendations, email lists with a specific audience in mind, gaming websites, online portals tied to consumer loyalty packages, consent-based networks, and social media platforms. Before participants join a panel, Qualtrics hires a

[117] lack of substitution possibilities in the IO model sector is the primary reason.

[118] possible extreme substitution effects and price changes is the ultimate cause.

[119] The research technique on this paragraph is written based on the ORDER-CRISP project documentation from Qualtrics and email correspondent with the Principal Investigator (PI) of ORDER-CRISP project.

[120] ESOMAR (www.esomar.org) publishes a Guideline for Online Research that covers ethical, methodological, regulatory, and legal issues in research technology.

third party to verify their names, addresses, and birthdates. Furthermore, Qualtrics used additional quality control measures to verify the participants, such as LinkedIn matching, business phone conversations, and third-party verification TrueSample, RelevantID, Verity, and so on. Therefore, we strictly adhered to the FIU Institutional Review Board (IRB) standard procedures for this paper's methodology.

We want to concentrate on the sampling procedure based on the ORDER-CRISP project documentation. To balance time and financial constraints, the Qualtrics company suggested a quota-based sample drawn from a non-probability online sample. Online survey sampling designs, recruitment techniques, and implementation procedures affect data quality and bias. To reduce bias, Qualtrics employs a variety of methods. Qualtrics drew the sample from over a million online survey participants. The survey aimed to appeal to a wide range of people. Qualtrics messages to participants include invitations to provide feedback to win a prize or earn money, among other things. Qualtrics omitted study specifics in their invitation to avoid self-selection bias. When the participant started the survey[121], Qualtrics supplied them with more information.

For data collection, Qualtrics employed cutting-edge software. The fieldwork manager oversaw the Texas data collection and led the survey setting up and testing. According to the IRB, Qualtrics obtained informed compliance consent from the respondents. The para-date described the details of the survey process and data collection. According to the US Census Bureau[122], " para-data can be seen as just a part of a survey,

[121] This paragraph excerpts from the ORDER-CRISP and Qualtrics project documentation.

[122] https://www.census.gov/newsroom/blogs/research-matters/2017/04/paradata.html

but they can also provide a deeper understanding of patterns in the survey data." The ORDER-CRISP project saved information like the type[123] of device, the user agent string, the time per question, the number of clicks per screen, the IP address, etc. The surveyed data underwent a series of screening processes for data cleaning and quality control. We removed the responses from respondents who answered grid questions in the same way and illogical answers to open-ended questions. In addition, we eliminated survey takers who had already completed the survey and those who provided inaccurate information about their household composition.

The population of the study consisted of 780 households in Texas that had been affected by Hurricane Harvey. From the population data, we decided to focus on the Houston MSA. To do so, we used GIS to locate the number of Houston respondents and reduced the final sample size of the Houston MSA to 500 households. We are attempting to obtain a quantifiable estimate of the percentage of homes affected by disruptions in their utility services, such as electricity, gas, phone/wireless connection, water, and transportation, with the help of our Hurricane Harvey household survey. We gathered information on the length of each utility interruption from respondents who had their utility service disrupted. Figure 3.2 depicts the selected 500 household units from Houston MSA.

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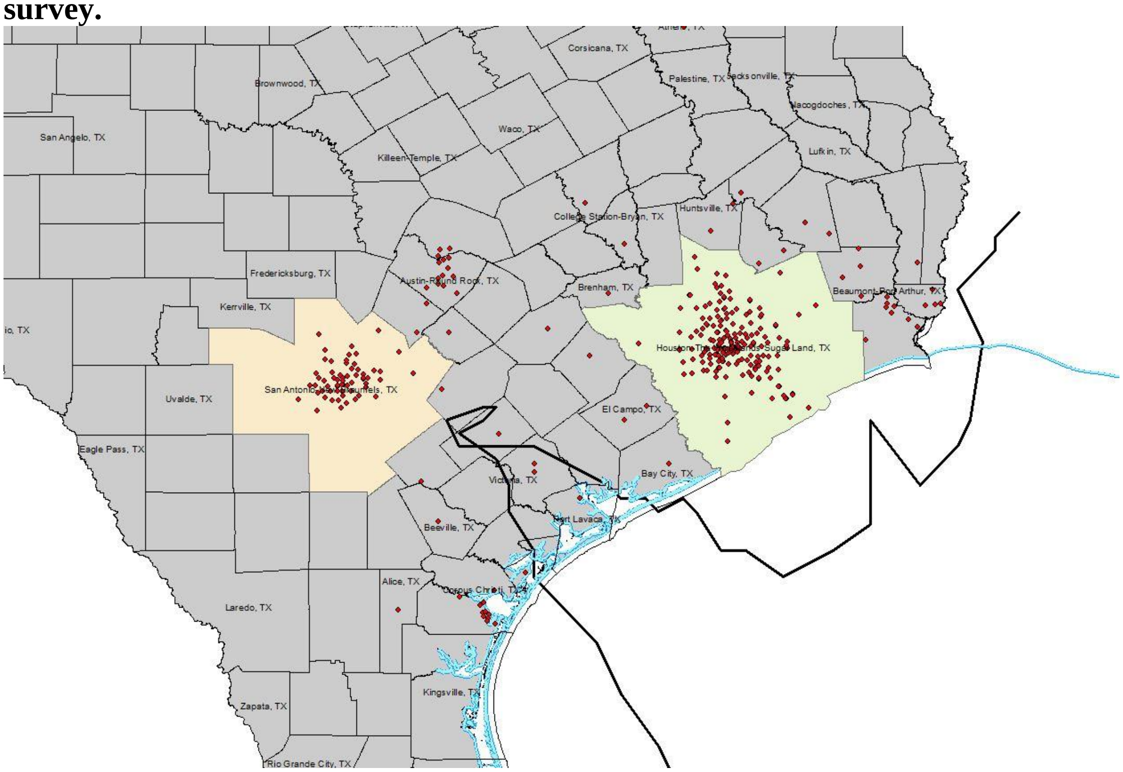
[123] ORDER-CRISP Project documentation summary help to formulate this paragraph.

Figure 3.2: Selected Houston household units from the Hurricane Harvey household survey.



Source: ORDER-CRISP Hurricane Harvey 2020 Household Survey.

3.4.1 Input-Output Tables and Their Integration for Analyzing Utility Disruption Impacts of Harvey:

Input-Output Model and Extensions

In an economy, critical infrastructures are like spider webs with a chain reaction. When one sector of the economy ceases to operate at its pre-hurricane level, it imposes costs on the economy's dependent sectors. Because temporary inoperability indirectly impacts the productive resources of dependent sectors, such costs must be measured carefully. When interdependent sectors fail to perform at pre-disaster levels, various methods and techniques are used to estimate the cataract effect of natural disasters. Kelly's (2015) paper discusses four approaches: econometrics, CGE modeling, IO models, and Cost-benefit analysis. Input-output models have become popular in recent years due to their ability to explain sectoral interdependencies and assess the cost of descending failure (Kelly, 2015). As a result, we chose to discuss Wassily Leontief's (Leontief, 1936) model and how it integrated into other disciplines.

Original Input-Output Model

The input-output model essentially depicts how various sectors of the economy are linked. The IO model's basic premise is that the output of one industry or sector is used as an input for other industries or sectors in the economy. The IO model's basic assumption is that the output of an industry is fully utilized across industries. Furthermore, Chiang & Wainwright (1984) made the following assumptions: each industry's input requirements are fixed, and production follows constant returns to scale in each sector. As a result, Table 3.1 present a basic IO table in matric format and shows the coefficient requirement.

Table 3.1. IO Coefficient matrix.

Input	Output				
	I	II	III	$\cdots$	N
I	a_{11}	a_{12}	a_{13}	$\cdots$	a_{1n}
II	a_{21}	a_{22}	a_{23}	$\cdots$	a_{2n}
III	a_{31}	a_{32}	a_{33}	$\cdots$	a_{3n}
$\vdots$	$\vdots$	$\vdots$	$\vdots$		$\vdots$
N	a_{n1}	a_{n2}	a_{n3}	$\cdots$	a_{nn}

Source: Chiang & Wainwright (1984)

The upper coefficient table may have a problem because this is an autarky situation that is utterly different in the presence of open economy dynamics. The households in the open economy model explain why consumers must have a final demand for each industry's final output in the open economy. As a result, the dynamic IO model takes the following form.

Table 3.2. complete IO model with the final demand.

$$\begin{bmatrix} (1-a_{11}) & -a_{12} & \cdots & -a_{1n} \\ -a_{21} & (1-a_{22}) & \cdots & -a_{2n} \\ \vdots & \vdots & & \vdots \\ -a_{n1} & -a_{n2} & \cdots & (1-a_{nn}) \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix}$$

Source: Chiang & Wainwright (1984)

Thus, Table 3.2 can be written in the following expression,

$$(\boldsymbol{I}-\boldsymbol{A})\boldsymbol{x}=\boldsymbol{d}$$

Where I is the identity matrix, A is the input required for each industry, x is the industry's output vector, and d is the final demand vector. The matrix *(I-A)* is known as the technology matrix. Hence, the output of an individual sector is estimated using the following equation,

$$\boldsymbol{x}=(\boldsymbol{I}-\boldsymbol{A_{arg}})^{-1}\boldsymbol{d}$$

Where,

x= final output of each sector

A_{arg}= Regional (Houston) technical coefficient matrix

d = Final demand matrix

I = Identity matrix

As a result, the IO model's one cell depicts how changes in one sector of the economy have ramifications throughout the economy. This concept is the foundation of our analysis, based on an extension of the original IO model. The DIIM model's concept is explained in the following subsection, as well as how it relates to measuring the ripple effect caused by the presence of a natural disaster.

3.4.2 Dynamic Inoperability Input-Output Model (DIIM):

The IO model predicts the change of one sector in the connected industry, as we mentioned in the previous subsection. Haimes & Jiang (2001) developed a generic risk (inoperability) model based on this concept. Their model assessed the impact of dynamic risk of inoperability on critical infrastructures. We need to integrate this Dynamic risk model with the economy's supply and use the table to get a meaningful interpretation. The value added by each industry is estimated in the supply and use table. As a result, we can calculate GDP using the sum of industry value added (income-based) or the cost of primary inputs across the economy (expenditure-based[124]).

Santos & Haimes (2005) developed the inoperability of an input-output model from the supply-use table. The authors order the economic sector based on a standard matrix operation (eigenvalue). However, their (Santos & Haimes) contribution opened a new avenue for replicating it in measuring the economic resiliency of interconnected and interdependent sectors, particularly for external shocks such as natural disasters. Flooding (Khalid & Ali, 2019, 2019; Yaseen et al., 2020; Yu et al., 2013), hurricanes (Akhtar & Santos, 2013a; Cimellaro et al., 2019), earthquakes (Huang et al., 2021), and other natural disasters impact have been estimated by DIIM..

Apart from natural hazard research, a variety of fields used DIIM, including healthcare (Robkin et al., 2015), quantum chemistry (Rossi et al., 2014), aeronautics (Brusa et al., 2014), land surface modeling (Kumar et al., 2006), computer science and electrical engineering (Kang & Chung, 2020; Nutaro, 2011), and many others. Our research attempts to represent the cascading effect of critical infrastructure sectors by estimating their

[124] https://www150.statcan.gc.ca/n1/pub/15-602-x/15-602-x2017001-eng.htm

inoperability. Our paper used the extension from Santos & Haimes's (2005) and Santos et el. (n.d.)'s original article.

Inoperability is similar to the irregular[125] operations of interdependent sectors during a natural disaster, such as hurricane Harvey in Houston. Irregularity revealed that a sectoral procedure differed from its total capacity. As a result, Santos & Haimes (2005) devised a scale of inoperability ranging from 0 to 1. A zero value represents a typical non-hurricane scenario in which a sector operates at full capacity. On the other hand, the value of one means that the industry is entirely non-functional during a hurricane's landfall.

Hence, our DIIM model for the Houston area is presented below and is based on Santos & Haimes (2005) and Santos (n.d.).

$$q(t+1) = q(t) + K[A^{*}q(t) + C^{*}(t) - q(t)] \dots\dots\dots\dots\dots\dots (1)$$

The following are the components that make up the formulation in equation (1): The inoperability vector at time *t+1* is represented by **q(*t+1*)**, whereas the inoperability vector at time *t* is represented by **q(*t*)**; **K** is the resilience matrix, which reflects the pace at which the sectors are anticipated to return to their regular operation; **A*** is the interdependency matrix, which describes the degree to which the sectors are dependent on one another; and **C*(*t*)** is the demand fluctuation at the time *t*. Note that time *t* corresponds to the interoperability before the hurricane's landfall and *t+1* reflects the inoperability after the landfall.

Santos et el. (2022) paper linked the interoperability with the household survey from hurricane Sandy. Hence, in our paper, we merged supply use tables from the Bureau of Economic Analysis with the base inoperability and their duration from the Texas

[125] Santos & Haimes (2005) termed as engineering reliability.

Household survey. We will talk more details about it in the subsequent paragraph. Santos et el. (n.d.) computed the before hurricane interoperability by relating the total output of sector (x_i) and dependency on the infrastructure (w_i), which is presented in equation (2). To captures the value of infrastructure's contribution per unit output of a sector($q_i(t)$), Santos et el. (n.d.) multiply it with the time-varying disruption factor $d_k(t)$.

$$q_i(t) = \left(\frac{w_i}{x_i}\right) d_k(t) \ldots\ldots\ldots\ldots\ldots \ (2)$$

The matrix-vector formulation of equation (2) is written in the following equation (3). Where $(\mathrm{diag}(x))^{-1}$ diagonal of the output vector of all sectors, *w* is the weight of the expenditure of each industry, $d_k(t)$ is instantaneous infrastructure disruption at time *t*, and *x* is the output of each sector.

$$\boldsymbol{q} = d_k(t) * (diag(\boldsymbol{x}))^{-1}\boldsymbol{w} \ldots\ldots\ldots\ldots\ldots (3)$$

We substituted the pre-hurricane inoperability in Eq. (1) from Eq. (3). The new equation (4) measures the inter-sector interdependent inoperability at time step t+1. Equation (4) reproduces the updated sectoral inoperability at time t+1. We estimated economic losses by multiplying the sectoral production output by the updated inoperability. The goal of our paper was to use the results of a Texas home survey to model critical infrastructure system disruptions and calculate system-wide inoperability and duration in the Houston MSA. We calculated the value of inoperability using survey data until the sectors reached complete operability. The vector $\boldsymbol{q_1}$ is the new inoperability in post-hurricane time.

$$\boldsymbol{q_1} = d_k(t) * (diag(\boldsymbol{x}))^{-1}\boldsymbol{w} + \boldsymbol{K}[\boldsymbol{A}^* d_k(t) * (diag(\boldsymbol{x}))^{-1}\boldsymbol{w} + \boldsymbol{C}^*(t) - d_k(t) * (diag(\boldsymbol{x}))^{-1}\boldsymbol{w}] \ldots\ldots (4)$$

As previously stated, we obtained the GDP sectoral composition data from the Bureau of Economic Analysis (BEA[126]). Because Hurricane Harvey made landfall in 2017, we gathered Houston MSA GDP data for 2017 (in current dollars). When we checked the Houston data, we discovered a few discrepancies in the missing sectoral composition. We then downloaded the State of Texas data to replace the missing numbers. The Houston GDP data set contains 92 sectors, but this paper employs the graphical user interface (GUI) model that Santos et al. (n.d.) developed.

The GUI computational model has 71 interconnected sectors. As a result, we calculated the proportion of each sector in the same sectoral total of US GDP. Then, we replaced those proportions in the Houston MSA data to account for missing data. Houston's total GDP is approximately $473 billion. Finally, we used the GUI computational model's sectoral inoperability, duration, and proportions to estimate the top losing sectors and rank them by dollar loss. The Texas survey of utility disruption from the ORDER-CRISP project module has 13 sectors, but we chose the top seven essential sectors for post-hurricane recovery. The following section presents the estimated results and descriptive statistics.

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[126] https://www.bea.gov/data/gdp

3.5. Empirical Findings:

3.5.0 Integrated Framework and Application to Hurricane Harvey:

3.5.1 Household Survey Data and Characteristics.

This study used household survey data of Hurricane Harvey-affected households in the United States' South-Central region in Texas. There were 780 responses in this Harvey's impact survey. The survey collected detailed household information, including property damage, evacuations, and utility outages. In this paper, we selected 500 people from the Houston Metropolitan Statistical Area (MSA), 64 percent of the total 780 respondents.

In Houston, 61% of the 500 respondents were female, while 34% were male. The average age of the participants was 38 years old. Approximately 56% of the participants were white, 16% were black, and 18% were Hispanic. Only 4% of those surveyed had less than a high school diploma, 17% had a high school diploma, 18% had a college degree, and 57% had a bachelor's degree. Fifty-five percent of those surveyed were married, while 33 percent were single.

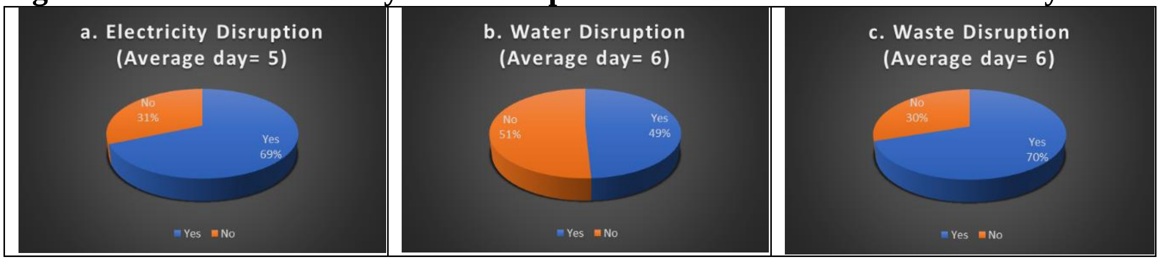
Eighteen percent of those surveyed were very liberal, while 13 percent were purely conservative. Following Hurricane Harvey's landfall, 66 percent of respondents had a paid job or were self-employed, compared to 78 percent before the storm. The respondents earned between $66,000 and $72,000 per year. Only 13% of those surveyed were tenants, while most respondents (87%) were homeowners. Half of the population lived in single-family homes, 9% in townhouses, and 11% in duplexes.

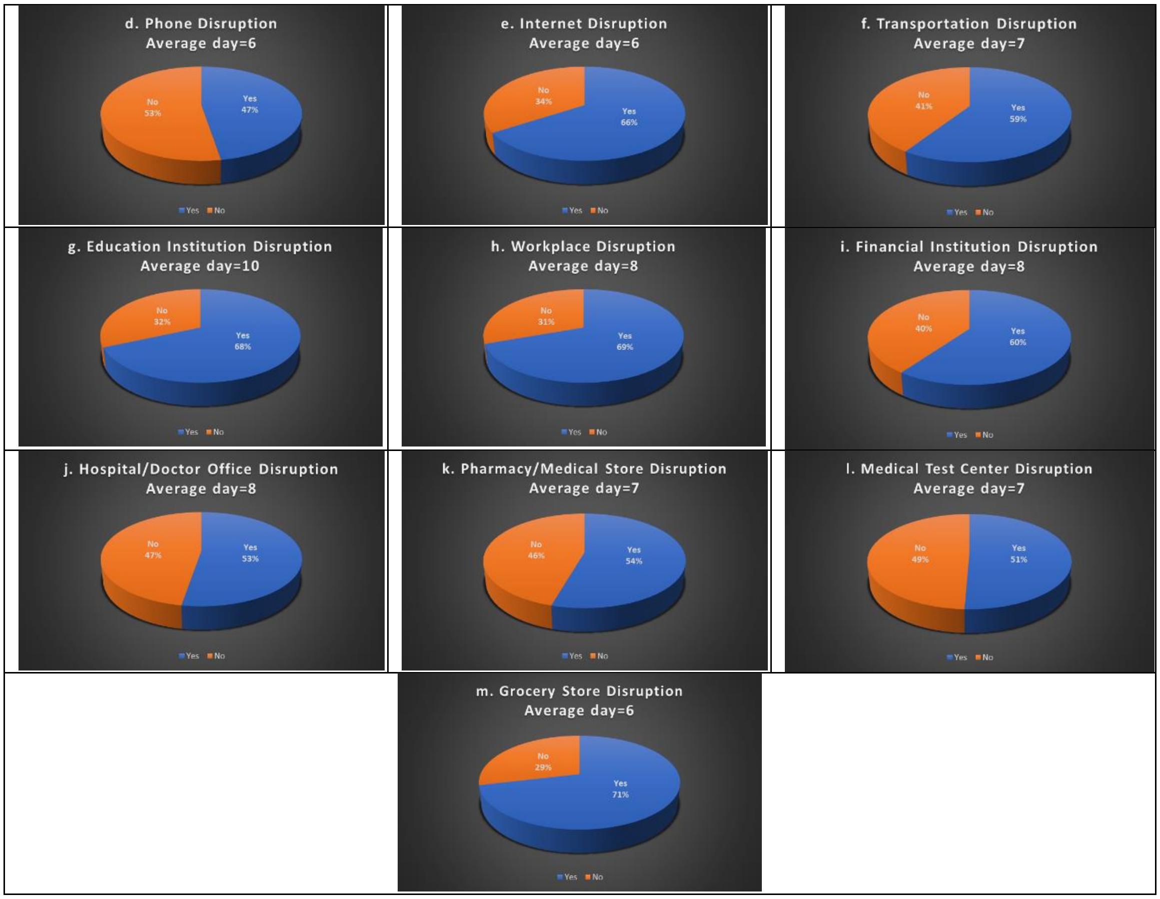
The survey respondents provided information on the thirteen utility disruptions they experienced during Hurricane Harvey. The categories are electricity, water, waste, phone, Internet, public transportation, educational institutions, workplace, financial institution, hospital/office, doctor's pharmacy/medical store, medical testing center, and grocery store. Approximately 69 percent of respondents reported a five-day electrical outage, while 49 percent reported a six-day water supply outage. Seventy percent reported limited garbage disposal options for six days, while 47 percent reported phone service outages. Again, 66 percent of households had difficulty accessing the Internet, and 59 percent could not travel by public transportation.

Again, 68% of educational institutions were closed or had limited access for up to ten days, and 69% of workers could not report to work for eight days. Then, for the next eight days, 60% of those affected were unable to access banks or financial institutions, and 53% were unable to see a hospital or their physician. Another 54% could not visit pharmacies/medical shops for seven days, while 51% were unable to visit medical testing centers.

Finally, nearly two-thirds of respondents (71%) reported being unable to purchase necessary household items. We depict the type and duration of disturbances in Figure 3.3a-m. In addition, respondents reported their evacuation and how long they evacuated during Hurricane Harvey. The average evacuation lasted 44 days, with 35.37 percent of respondents packing their belongings.

Figure 3.3: Infrastructure System Disruption as a result of Hurricane Harvey.

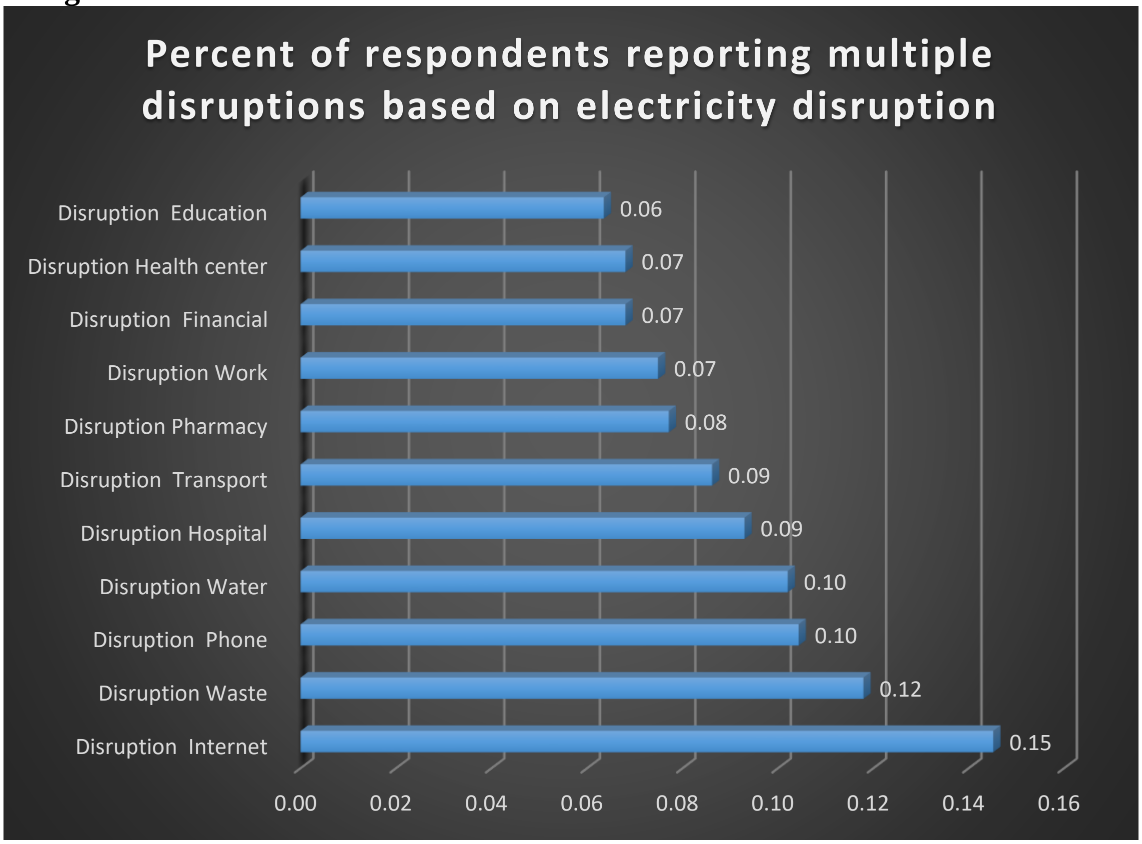




The majority who responded to the survey likely encountered cascading failures, which may have been caused primarily by a power failure. Figure 3.4 depicts the homes affected by various interruptions during Harvey, listed in decreasing order concerning power disruption. Before this, we reported that 69 percent of respondents had experienced a power outage. There was 15 percent who experienced internet disturbance, followed by garbage (12 percent), and phone and water each accounted for ten percent of the disruptions in this group.

Power outages caused the most disruption in the health care industry, accounting for 24 percent of hospitalizations, pharmacy visits, and doctor's appointments. However, only 7% of the homes that experienced power outages were in the workplace or financial industry.

Figure 3.4: Percent of respondents reported multiple disruptions based on power outages.



People affected by the power outage also had difficulty obtaining alternative modes of transportation (9 percent). Only a power outage and a school disruption accounted for the smallest share of all disorders (6 percent). As a result, the interdependence of critical infrastructure explains the need to estimate the economic damage caused by Hurricane Harvey in the Houston area.

3.5.2 Dynamic Inoperability Input-Output Model (DIIM) Results.

The DIIM is a novel extension of the original input-output model. The estimated results in this paper came from the graphical user interface (GUI) model of the ORDER-CRISP project. Santos et al. (n.d.) created this DIIM model. From the 2020 survey, we got the average interoperability and duration (recovery period) parameters.

Then, we put both numbers into the DIIM model. The DIIM contains 71 economic sectors derived from the Bureau of Economic Analysis's (BEA) 2017 current year GDP for the Houston MSA area. The DIIM module includes functions that can input the value of critical infrastructure (for example, transportation, electricity, water, and so on).

We created a top ten critically affected sectors from the GUI analysis by economic loss and interoperability. Hence, the GUI interface captured the parameter's value in the modules after imputing the survey parameters into the DIIM model. The dual input necessitates a single infrastructure's initial inoperability and recovery time (days).

We analyzed the Texas 2020 survey data and 13 infrastructure systems as per the survey's disruption module. Table 3.3 describes the base inoperability and recovery periods. In our analysis, we defined inoperability as the average number of responses who experienced certain types of utility disruption during Hurricane Harvey.

The duration of disruption following Hurricane Harvey's landfall determines each respondent's recovery period. One notable departure in our paper from Santos et al. (n.d.) is that we did not separate the transportation sector into a truck or general ground transportation.

Table 3.3. Household Survey Direct Disruption Inputs to the DIIM.

Service Systems	Base inoperability (percent)	Days until recovery
1. Electricity	69	5
2. Water	49	6
3. Waste disposal	70	6
4. Phone/Cell phone	47	6
5. Internet	66	6
6. Public transportation	59	7
7. Education	68	10
8. Workplace	69	8
9. Financial institutions	60	8
10. Hospitals/doctor’s office	53	8
11. Pharmacy/medical stores	54	7
12. Medical test centers	51	7
13. Grocery stores	71	6

Source: ORDER-CRISP Hurricane Harvey 2020 Household Survey. The Houston Metropolitan Statistical Area included 500 homes (MSA). Base inoperability was calculated as a percentage of 500 households with a single utility outage during Harvey.

In the DIIM GUI module, we calculated seven different scenarios and gave each one a detailed description. We chose seven out of the 13 sectors because we believed they were the most important during the post-Harvey period. The leading seven infrastructures in our analysis are workplace, water, electricity, grocery, transportation, Internet, and phone/cell phone (labeled as telecom). We ran seven individual inoperable analyses. Finally, we combined the seven scenarios into a single DIIM that calculated the total monetary losses (in 2017 million dollars). We present the key findings from an individual (static[127]) scenario in the following sub-sections, 5.2.1-7, and discuss the aggregate (integrated) sector scenario in the last sub-section, 5.3.0.

3.5.2.1. Power (Electricity) Sector Interoperability Analysis.

All seven sectors of our analysis require electricity. The power sector, for example, includes facilities that produce, transfer, and allocate electricity, gas, or steam, which can account for a $4 billion loss in the event of simulated high-elevation nuclear explosions (Crowther et al., 2007; Haimes et al., 2005; MacKenzie & Barker, 2013). A similar synopsis of electricity outage economic losses can be found in the literature by Yoon et al. (2019). In our paper, the electricity was only 31% operational; thus, we obtained 69 percent interoperability that lasted up to 5 days until the service was restored, presumably in the Houston area. In Table 3.4, we presented the top ten inoperable sectors because of electric sector disruption and the top ten industries with the greatest economic loss.

Table 3.4. The ten inoperable sectors and the ten economically impacted industries in the event of a five-day power outage in Houston.

Top 10 Sectors (Inoperability)
Warehousing and storage
Primary metals
Plastics and rubber products

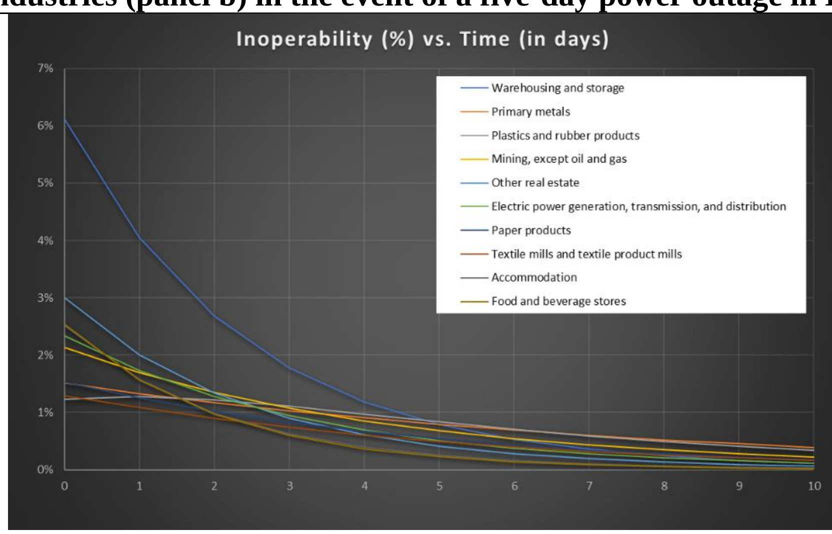
Top 10 Sectors (Economic Loss)	Loss ($,000)
Chemical products	7,999
Paper products	3,898
Electric power generation, transmission, and distribution	3,312

[127] Static in the sense that other six sector inoperability is assumed to be constant.

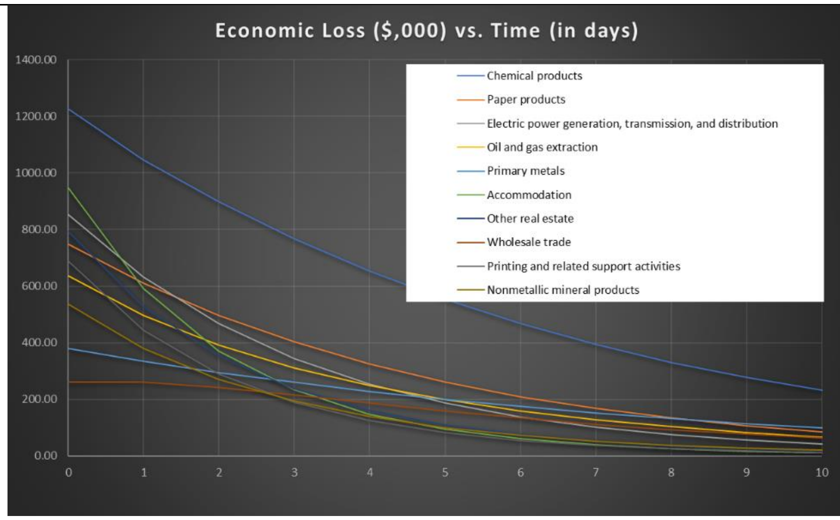
Mining, except oil and gas	Oil and gas extraction	3,115
Other real estates	Primary metals	2,946
Electric power generation, transmission, and distribution	Accommodation	2,564
Paper products	Other real estates	2,438
Textile mills and textile product mills	Wholesale trade	2,102
Accommodation	Printing and related support activities	2,000
Food and beverage stores	Nonmetallic mineral products	1,904
	Total Loss (includes top 10 + remaining 61 sectors)	58,078

Table 3.4 shows that the top two inoperable sectors were warehousing, storage, and primary metals; we also see that the power outage impacted electric power generation. When we looked at the top ten economic loss sectors, we discovered that chemical products were worth \$8 million, and paper products were worth \$4 million. Power generation alone was worth more than \$3 million. The Houston economy suffered a total production loss of \$58 million when we added the 71 sectors. Figure 3.5 depicts a diagram of the inoperability and top ten economic losses.

Figure 3.5: The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in the event of a five-day power outage in Houston.



Panel (a)



Panel (b)

According to Figure 3.5, the top ten inoperable sectors had 1-6 percent less capacity than their total capacity immediately after Hurricane Harvey's landfall. They had dropped to less than 1% by the tenth day. Furthermore, the top ten sectors' direct economic losses ranged from over $200 thousand to $1.2 million immediately following the landfall. We observed a reduction in financial loss (less than $200 thousand) on the tenth day after the landfall,

3.5.2.2. Water Disruption Interoperability Analysis.

Water disruption hurts all aspects of life, from humans to production, and fresh drinking water is essential for the population immediately following a natural disaster. We ran the GUI module's water sector inoperability and showed the summary of the results in Table 3.5.

Table 3.5. The ten most inoperable sectors and the ten most economically impacted industries in the event of a six-day water disruption in Houston.

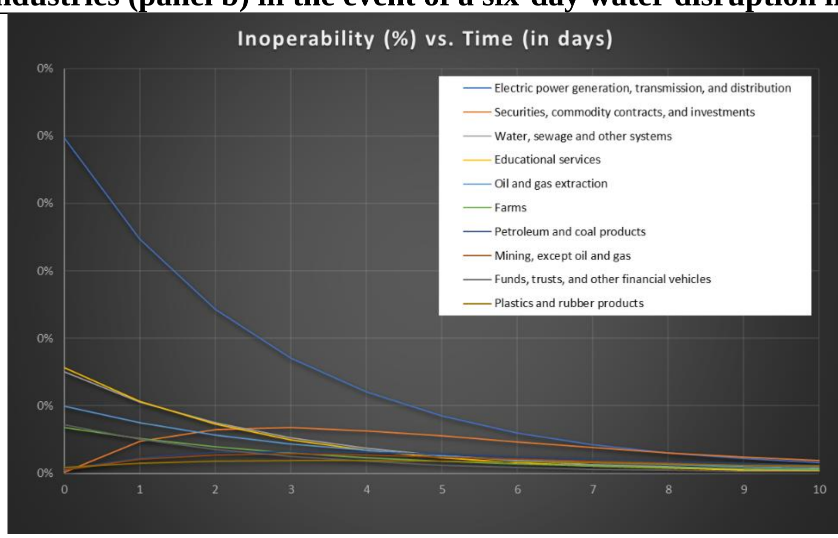
Top 10 Sectors (Inoperability)	Top 10 Sectors (Economic Loss)	Loss ($,000)
Electric power generation, transmission, and distribution	Electric power generation, transmission, and distribution	307
Securities, commodity contracts, and investments	Oil and gas extraction	251
Water, sewage, and other systems	Chemical products	130
Educational services	Funds, trusts, and other financial vehicles	80

Oil and gas extraction	
Farms	
Petroleum and coal products	
Mining, except oil and gas	
Funds, trusts, and other financial vehicles	
Plastics and rubber products	

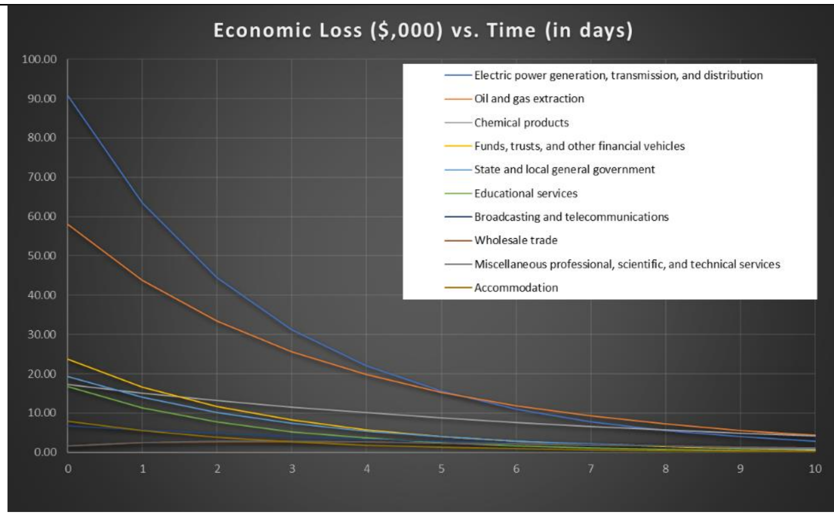
State and local general government	72
Educational services	53
Broadcasting and telecommunications	41
Wholesale trade	29
Miscellaneous professional, scientific, and technical services	28
Accommodation	27
Total Loss (includes top 10 + remaining 61 sectors)	1,518

According to Table 3.5, the total economic loss from water inefficiency is around $1.5 million, with electric power generation, transmission, and distribution suffering the most significant loss of $307 thousand. In comparison, accommodation sustained a loss of less than $30,000. Aside from this finding, when we look at the top ten sectors of interoperability, we find that electric power generation, transmission, and distribution had the most interoperability, followed by securities, commodity contracts, and investments. The breakdown of inoperability revealed that four of the top ten industries were from manufacturing, while only one (education) was from the service sector. Figure 3.6 shows a diagram of the Houston MSA area's inoperability and top ten economic losses.

Figure 3.6: The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in the event of a six-day water disruption in Houston.



Panel (a)



Panel (b)

When we looked at the top panel (a) for the inoperability of a possible range of values, we couldn't find one. Our skepticism prompted us to conduct additional research, so we returned to the GUI module and investigated the vertical axis property. Because the GUI module generates interoperability values automatically, we observed a lower boundary of 0.001 and a major boundary of 0.005. This context led us to conclude that the Houston population and the water-dependent productive sector did not experience much water inoperability following Hurricane Harvey. On the first day after Harvey, we saw a contrasting scenario of economic loss in panel (b). The topmost sector suffered losses of up to $90,000, confirming that water disruption had a minor cascading effect on the Houston MSA.

3.5.2.3. Telecom Sector Interoperability Analysis.

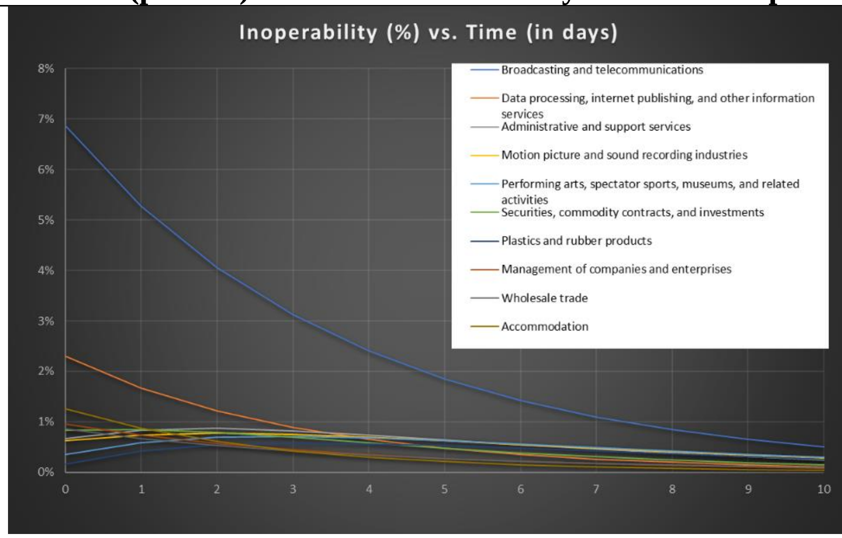
Houston's telecommunications sector was operating at 53% capacity, and customers faced a six-day outage. In our survey data, telecom disruptions include both landline and cell phone disruptions. Telecom is critical for telecommunications, retail businesses, and online shopping, particularly since the rapid development of touch-screen-based cell phones. Table 3.6 shows the top ten inoperable and economic loss sectors.

The top ten inoperable sectors revealed that nine of the ten require extensive backward linkage of the telecom industry. Broadcasting, data processing, and administrative support services, for example, relied heavily on telecom support. During the first ten days of telecom sector inoperability, the telecom sector caused a $65 million loss in GDP. The broadcasting and telecommunications sectors lost $18 million in productive capacity out of that $65 million. We present the two parameters in figure 3.7 for further elaboration.

Table 3.6. The ten most inoperable sectors and the ten most economically impacted industries in the event of a six-day telecom disruption in Houston.

Top 10 Sectors (Inoperability)		**Top 10 Sectors (Economic Loss)**	**Loss ($,000)**
Broadcasting and telecommunications		Broadcasting and telecommunications	18,355
Data processing, internet publishing, and other information services		Legal services	3,858
Administrative and support services		Miscellaneous professional, scientific, and technical services	2,999
Motion picture and sound recording industries		Federal Reserve banks, credit intermediation, and related activities	2,754
Performing arts, spectator sports, museums, and related activities		Data processing, internet publishing, and other information services	2,404
Securities, commodity contracts, and investments		Insurance carriers and related activities	2,166
Plastics and rubber products		Wholesale trade	2,053
Management of companies and enterprises		State and local general government	1,991
Wholesale trade		Publishing industries, except internet (includes software)	1,908
Accommodation		Chemical products	1,891
		Total Loss (includes top 10 + remaining 61 sectors)	64,946

Figure 3.7: The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in the event of a six-day telecom disruption in Houston.



Panel (a)

Panel (b)

Some notable findings from telecom sector disruptions immediately after hurricane Harvey are that only three sectors were functioning above the 2 percent level of their regular business operation. Seven of the top ten disrupted sectors were inoperable at less than 2 percent, particularly below one percent. If we look at the progression of broadcasting and telecommunication services alone, the first four days cost approximately $12 million of missing value addition to the GDP. A closer examination of the loss in Table 3.6 reveals that the top ten sectors' minimum cost was over $1 million.

3.5.2.4. Internet Service Interoperability Analysis.

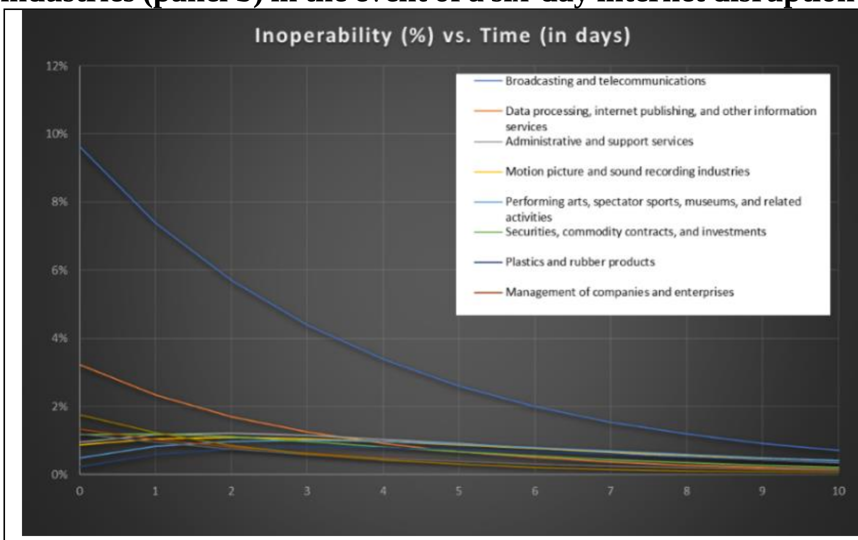
The Internet's significance is universal. Two-thirds of users consider the Internet a vital or significant information source, with 80 percent using it for Web surfing and browsing and adults spending more than a quarter of their time online looking for information (Haythornthwaite, 2001). Following that, 66% of Houston MSA respondents reported internet outages during Hurricane Harvey, with some residents reporting outages lasting up to 6 days. Figure 3.8 depicts the cascading effect of disruption and the economic loss value.

Table 3.7. The ten most inoperable sectors and the ten most economically impacted industries in the event of a six-day internet disruption in Houston.

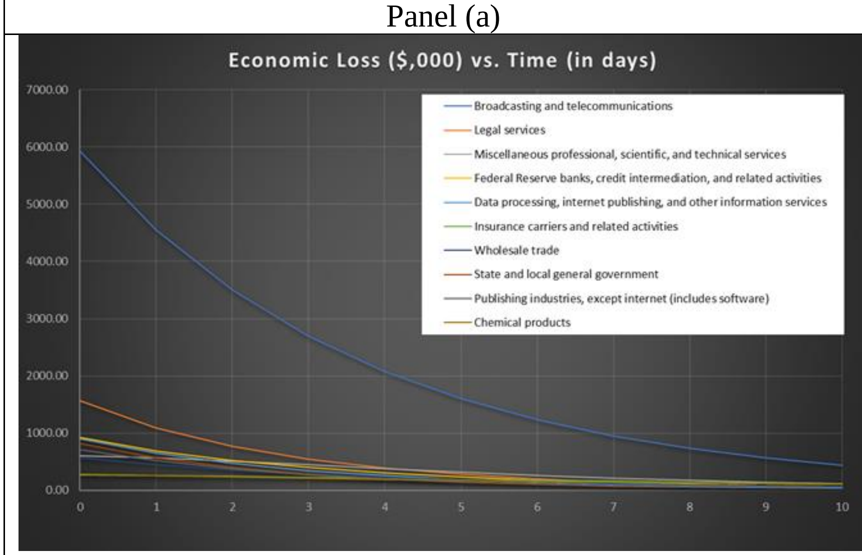
Top 10 Sectors (Inoperability)		Top 10 Sectors (Economic Loss)	Loss ($,000)
Broadcasting and telecommunications		Broadcasting and telecommunications	25,774
Data processing, internet publishing, and other information services		Legal services	5,418
Administrative and support services		Miscellaneous professional, scientific, and technical services	4,211
Motion picture and sound recording industries		Federal Reserve banks, credit intermediation, and related activities	3,867
Performing arts, spectator sports, museums, and related activities		Data processing, internet publishing, and other information services	3,376
Securities, commodity contracts, and investments		Insurance carriers and related activities	3,041
Plastics and rubber products		Wholesale trade	2,882
Management of companies and enterprises		State and local general government	2,796
Wholesale trade		Publishing industries, except internet (includes software)	2,679
Accommodation		Chemical products	2,655
		Total Loss (includes top 10 + remaining 61 sectors)	91,201

Currently, most of the streaming and broadcasting takes place over the Internet. That was evident in panel (a), where broadcasting and telecommunications providers operated at 90% of their capacity following the hurricane. In contrast, the rest of the sector ran at less than 4% of its standard capacity. The monetization of that ten percent interoperability costs $6 million in panel fees to broadcasting and telecommunications services (b). The reduced functionality of the federal reserve bank, credit intermediation, and related activities, as well as state and general government, is a unique find. Table 3.7 shows that the total economic efficiency loss was $91 million in the first ten days, with telecommunications and broadcasting topping the list with $26 million.

Figure 3.8: The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in the event of a six-day internet disruption in Houston.



Panel (a)



Panel (b)

3.5.2.5. Public Transportation Interoperability Analysis.

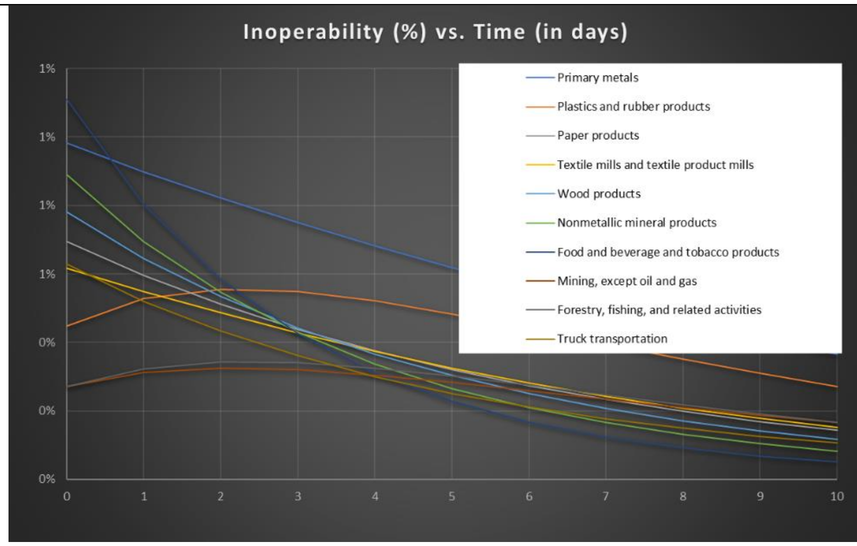
BEA GDP data include various types of public transportation, but for our paper, we focused on ground and truck transportation as a combination of public transit. The Houston MSA stalled for about seven days when Harvey disrupted the public transportation system. The sector was 59 percent inoperable. Table 3.8 shows the results.

Table 3.8. The ten most inoperable sectors and the ten most economically impacted industries in the event of a seven-day transportation disruption in Houston.

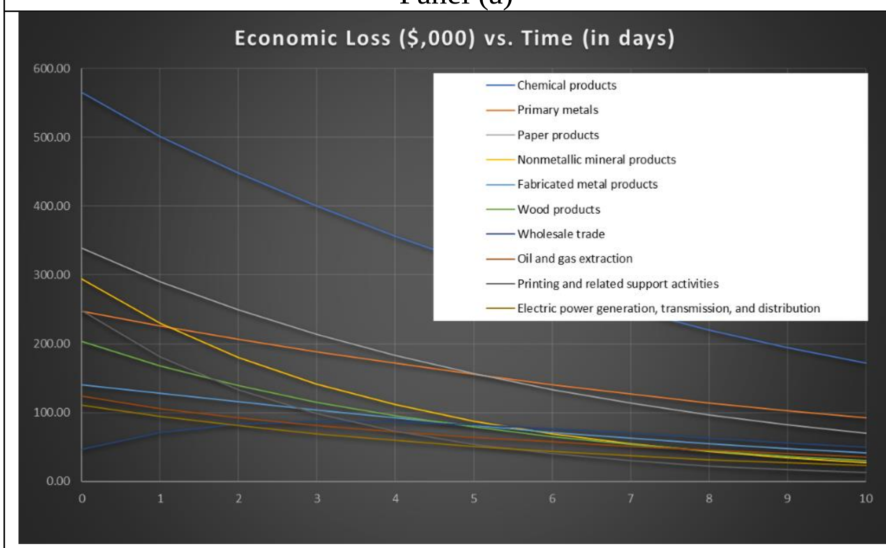
Top 10 Sectors (Inoperability)		**Top 10 Sectors (Economic Loss)**	**Loss ($,000)**
Primary metals		Chemical products	4,930
Plastics and rubber products		Primary metals	2,515
Paper products		Paper products	2,332
Textile mills and textile product mills		Nonmetallic mineral products	1,392
Wood products		Fabricated metal products	1,204
Nonmetallic mineral products		Wood products	1,178
Food and beverage and tobacco products		Wholesale trade	1,118
Mining, except oil and gas		Oil and gas extraction	1,032
Forestry, fishing, and related activities		Printing and related support activities	956
Truck transportation		Electric power generation, transmission, and distribution	776
		Total Loss (includes top 10 + remaining 61 sectors)	29,386

The total economic loss from 71 sectors is around $29 million, with the loss from each sector estimated as $12 million. As a result, the collective loss from public transportation is much smaller than the loss from the Internet. Still, when we dig deeper, the range of sectors varies from manufacturing to the wholesale trade. The loss range is much more comprehensive than in any previous industry. Figure 3.9 depicts the ranking of inoperability. According to diagram 3.9, the average operability was one percent. Furthermore, truck transportation and the plastic and rubber industries experienced increased inoperability in the first two days before gradually decreasing. After the fifth day of the hurricane, the economic loss progression shows a rapid decrease.

Figure 3.9: The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in the event of a seven-day transportation disruption in Houston.



Panel (a)



Panel (b)

3.5.2.6. Workplace Interoperability Analysis.

Natural disasters hurt the economy and the labor force, i.e., the active workplace. Due to hurricane devastation and other related infrastructure failures, most workstations were closed. Akhtar & Santos (2013a) conducted a DIIM analysis based on regional workplace disruption to determine the rank of inoperability and economic loss. Our paper estimation strategy is similar to theirs, and Table 3.9 summarizes workplace rigidity.

The DIIM projection is a simulated prediction that sheds light on the possible inoperability. A closer examination of Table 3.9 and figure 3.10 reveals that the top inoperable sectors (such as food and beverage) were less functional at more than 400 percent.

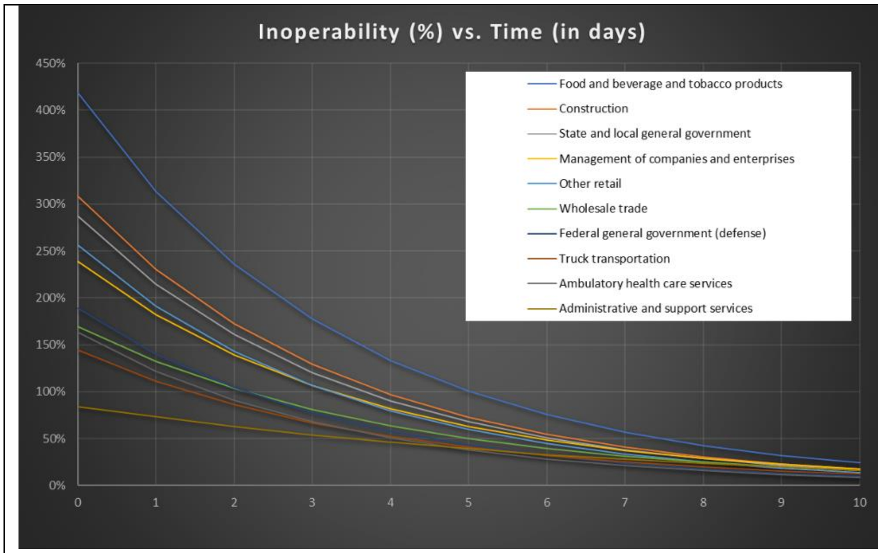
Table 3.9. The ten most inoperable sectors and the ten most economically impacted industries in the event of an eight-day workplace disruption in Houston.

Top 10 Sectors (Inoperability)		Top 10 Sectors (Economic Loss)	Loss ($,000)
Food and beverage and tobacco products		State and local general government	846,734
Construction		Wholesale trade	381,743
State and local general government		Miscellaneous professional, scientific, and technical services	250,713
Management of companies and enterprises		Construction	157,851
Other retail		Insurance carriers and related activities	134,317
Wholesale trade		Federal general government (defense)	116,991
Federal general government (defense)		Chemical products	104,737
Truck transportation		Computer systems design and related services	96,862
Ambulatory health care services		Federal Reserve banks, credit intermediation, and related activities	90,347
Administrative and support services		Truck transportation	85,787
		Total Loss (includes top 10 + remaining 61 sectors)	3,827,409

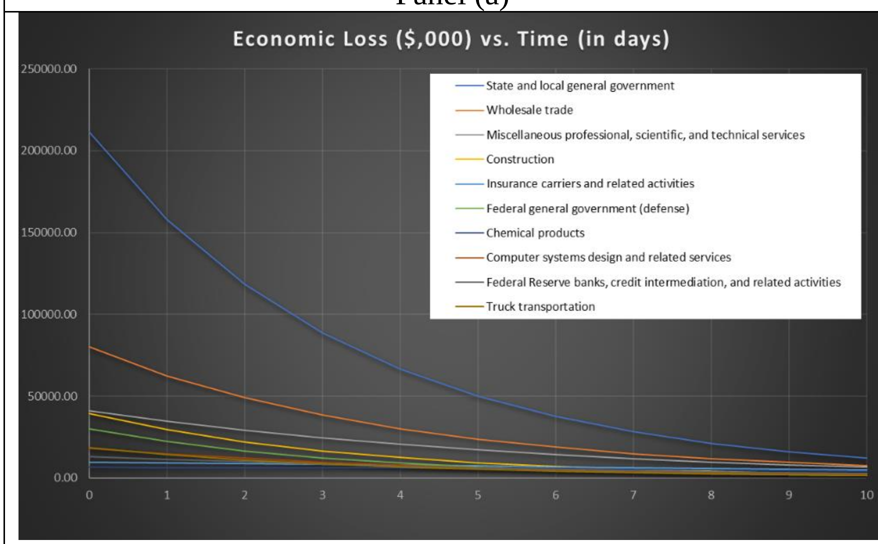
In comparison, construction was inoperable at more than 300 percent. State and local governments are closer to 300 percent, while the rest are more than 80 percent nonfunctional. Higher levels of inoperability imply more massive GDP loss projections. Table 3.9 lists workplace disruption as one of the top ten economic losses, with a total loss of approximately $4 billion. State, local, and defense governments lost roughly $1 billion.

The wholesale trade could be worth $382 million, professional services could be worth $250 million, and truck transportation could be worth $86 million. The projection of these results in figure 3.10 panel (b) shows that the state and local governments lost $250 million immediately following the hurricane's landfall. Given the eight-day duration of inoperability, this projection is unthinkable, but it may indicate policymakers' willingness to take precautionary measures in the face of hurricane damage.

Figure 3.10. The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in the event of an eight-day workplace disruption in Houston.



Panel (a)

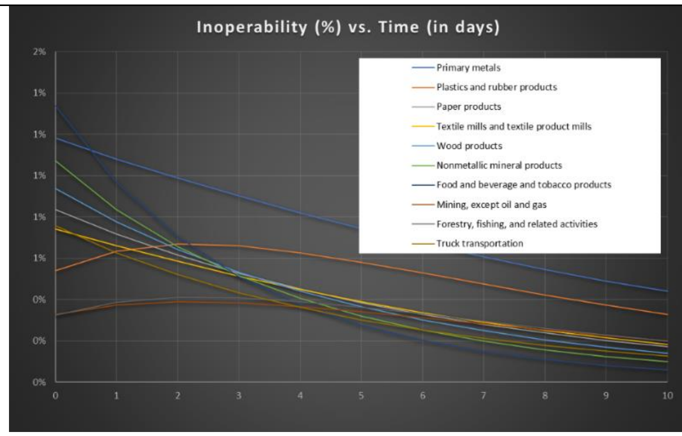


Panel (b)

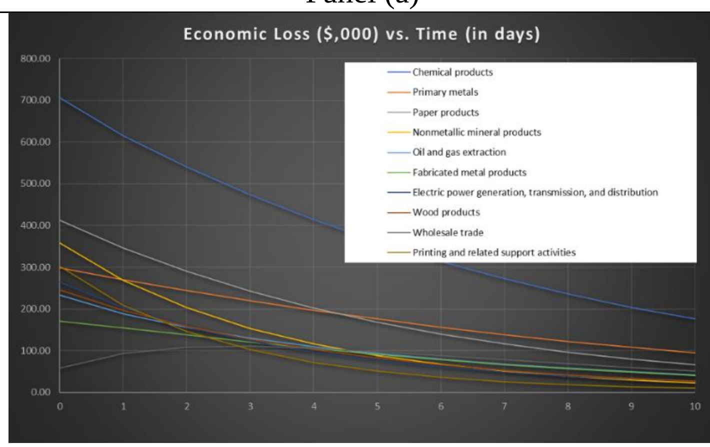
3.5.2.7. Grocery Interoperability Analysis.

The previous subsection's pattern of possible wholesale loss ($250 million) prompted the need to assess inoperability and economic loss at the retail level. As a result, the survey asked respondents about their grocery store access interruption. Seventy-one percent of them reported disruptions in grocery access that lasted six days. We entered these two parameters into the GUI module to generate the inefficiency and economic loss chart shown in Figure 3.11.

Figure 3.11: The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in the event of a seven-day grocery disruption in Houston.



Panel (a)



Panel (b)

According to Figure 3.11, the cascading effect of stillness in the grocery sector primarily affected chemical, metal, wood, and paper products. The interoperability spillover effect was roughly less than 1%. Even on the tenth day, the economic loss from retail trade disruption continued to be significant for the chemical product ($0.2 million approx.).

Table 3.10 shows that the combined loss of the top ten and 61 sectors was $31 million. Metal product value is lost by about $5 million in that $31 million, while wholesale trade costs $1.2 million. The absence of food and beverage from the top ten losses was notable because we expected the demand for food and beverage to increase following the hurricane.

Table 3.10. The ten most inoperable sectors and the ten most economically impacted industries in the event of a seven-day grocery disruption in Houston.

Top 10 Sectors (Inoperability)		Top 10 Sectors (Economic Loss)	Loss ($,000)
Primary metals		Chemical products	5,192
Plastics and rubber products		Primary metals	2,648
Paper products		Paper products	2,456
Textile mills and textile product mills		Nonmetallic mineral products	1,466
Wood products		Fabricated metal products	1,267
Nonmetallic mineral products		Wood products	1,241
Food and beverage and tobacco products		Wholesale trade	1,177
Mining, except oil and gas		Oil and gas extraction	1,087
Forestry, fishing, and related activities		Printing and related support activities	1,007
Truck transportation		Electric power generation, transmission, and distribution	817
		Total Loss (includes top 10 + remaining 61 sectors)	30,947

3.5.3. Integrated Sectors Interoperability Analysis.

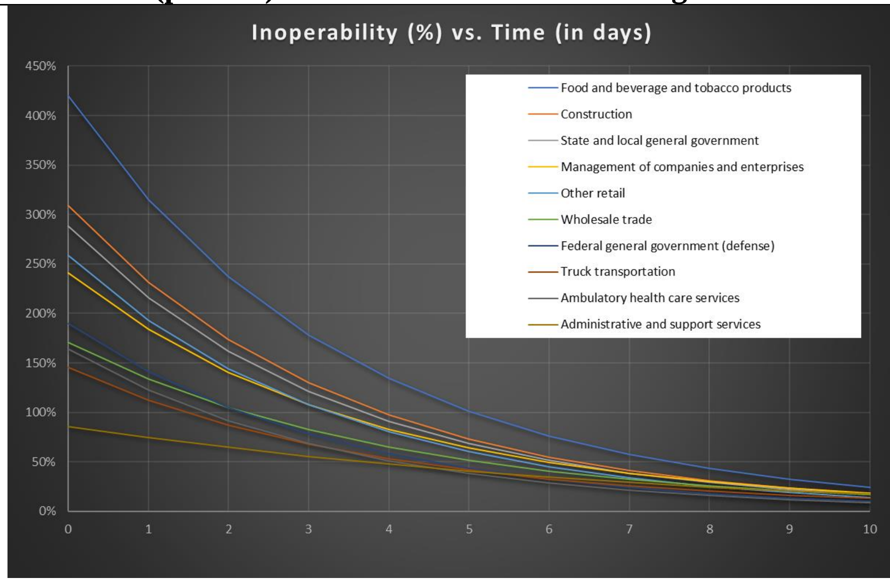
As a static case, we set other sector inoperability to zero at the start of the individual sectoral interoperability analysis. However, this is not a realistic assumption in the context of Hurricane Harvey. A hurricane of varying magnitude and duration strikes all sectors simultaneously. We could also track the variability of the top ten sectors' inoperability or loss. An integrated (per se dynamic) GUI analysis could narrow the list and generate the most realistic case of GDP loss in Houston after Hurricane Harvey in 2017. Table 3.11 shows the top ten inoperable sectors identified by the integrated analysis. We divided our investigation into two parts. We will first analyze it similarly to the previous sub-sections and then compare it to the workplace disruptions alone. Once we have completed the comparative analysis, we will clarify the rationale for that comparison.

Table 3.11. The ten most inoperable sectors and the ten most economically impacted industries in the event of an integrated sectors disruption in Houston.

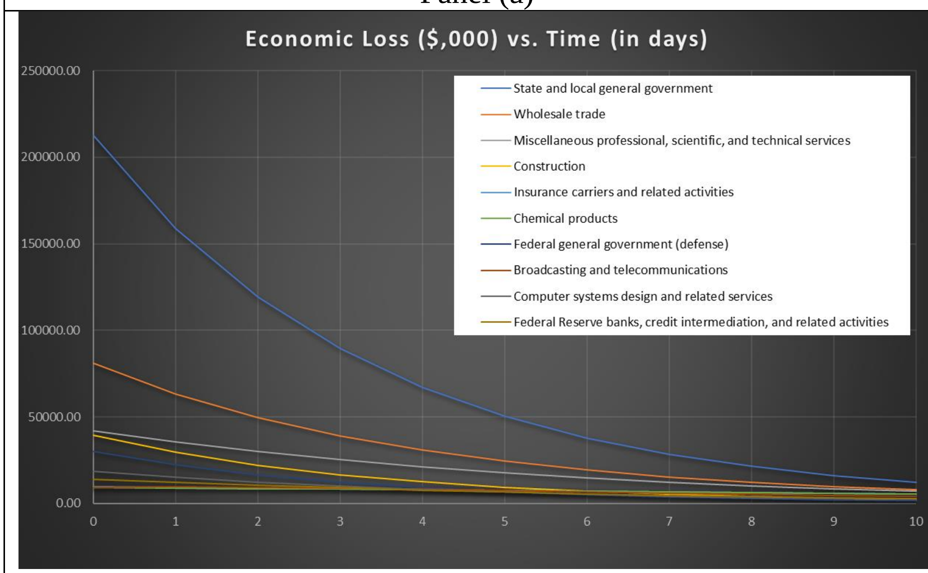
Top 10 Sectors (Inoperability)		Top 10 Sectors (Economic Loss)	Loss ($,000)
1. Food and beverage and tobacco products		State and local general government	852,470
2. Construction		Wholesale trade	389,753
3. State and local general government		Miscellaneous professional, scientific, and technical services	258,121
4. Management of companies and enterprises		Construction	158,465
5. Other retail		Insurance carriers and related activities	139,164
6. Wholesale trade		Chemical products	130,930
7. Federal general government (defense)		Federal general government (defense)	117,538
8. Truck transportation		Broadcasting and telecommunications	104,728
9. Ambulatory health care services		Computer systems design and related services	99,338
10. Administrative and support services		Federal Reserve banks, credit intermediation, and related activities	96,133
		Total Loss (includes top 10 + remaining 61 sectors)	4,065,937

Table 3.11 suggests a potential loss of $4 billion. State and local governments would lose $1 billion in addition to the federal government (defense). The wholesale operated GDP loss is $390 million, followed by Miscellaneous professional, scientific, and technical services ($258 million), construction ($158 million), and the rest of the losses are close to $100 million or more. Figure 3.12 depicts the top ten inoperable sectors, ranging from 50 percent (admin and support service) to 420 percent (food, beverage, and tobacco) immediately after the landfall. On the same day, the economic loss reached $2 million. On the tenth day after the landfall, the inability of ten sectors and the financial failure of the top ten interconnected sectors gradually converge.

Figure 3.12: The ten most inoperable sectors (panel a) and the ten most economically impacted industries (panel b) in Houston's event of an integrated sectors disruption.



Panel (a)



Panel (b)

During the analysis phase, we were surprised by the similarity between integrated interoperability and single (workplace) inoperability. This context prompted us to conduct a comparison of the two incompatibilities. Table 3.12 divides the top ten rankings of interoperability into two columns. Comparing the top ten economic loss sectors, we conclude that their orders are identical. We believe their top inoperability is the same. This finding may explain why workplace inefficiency is the leading cause of the Houston economy's deterioration (GDP loss). We want to clarify that workplace disruption does not always imply wage loss for workers and their connection to the economy's supply-side multiplier effect. Table 3.13 details the loss comparison.

Table 3.12. Comparison of integrated vs. workplace inoperability.

Integrated Disruption Inoperability		Workplace Disruption Inoperability
Top 10 Sectors		**Top 10 Sectors**
1. Food and beverage and tobacco products		1. Food and beverage and tobacco products
2. Construction		2. Construction
3. State and local general government		3. State and local general government
4. Management of companies and enterprises		4. Management of companies and enterprises
5. Other retail		5. Other retail
6. Wholesale trade		6. Wholesale trade
7. Federal general government (defense)		7. Federal general government (defense)
8. Truck transportation		8. Truck transportation
9. Ambulatory health care services		9. Ambulatory health care services
10. Administrative and support services		10. Administrative and support services

We predicted the same economic loss because the top ten inoperable sectors were identical in the Table 3.12 comparison. As a result, we created a monetary loss in Table 3.13 similarly. We discovered that broadcasting and telecommunications were in the integrated column, whereas truck transportation was in the workplace column, after investigating the two columns of loss sectors.

Table 3.13. Comparison between integrated and single sector disruption economic loss.

Integrated/Multi-sector Disruption (Economic Loss)			Single Sector Disruption (Economic Loss)		Net difference
Top 10 Sectors	**Loss ($,000)**		**Top 10 Sectors**	**Loss ($,000)**	**Integrated – Workplace ($,000)**
State and local general government	**852,470**		State and local general government	**846,734**	5,736
Wholesale trade	**389,753**		Wholesale trade	**381,743**	8,010
Miscellaneous professional, scientific, and technical services	**258,121**		Miscellaneous professional, scientific, and technical services	**250,713**	7,408
Construction	**158,465**		Construction	**157,851**	614
Insurance carriers and related activities	**139,164**		Insurance carriers and related activities	**134,317**	4,847
Chemical products	**130,930**		Chemical products	**104,737**	26,193

Federal general government (defense)	**117,538**
Broadcasting and telecommunications	104,728
Computer systems design and related services	**99,338**
Federal Reserve banks, credit intermediation, and related activities	**96,133**
Total Loss (includes top 10 + remaining 61 sectors)	4,065,937

Federal general government (defense)	**116,991**	547
Truck transportation	**85,787**	18,941
Computer systems design and related services	**96,862**	2,476
Federal Reserve banks, credit intermediation, and related activities	**90,347**	5,786
Total Loss (includes top 10 + remaining 61 sectors)	3,827,409	238,528 ($80M from top ten)

Note. We reorganized the top ten list to compute the difference.

We wanted to compare the loss, so we rearranged the sectors regardless of position or value to generate a net difference. According to the comparison, the integrated interoperability loss (valued at $4.065 billion) is $238 million greater than the workplace loss ($3.827 billion).

We were curious to learn which industry contributed to the disparity. We discovered that nine of the ten integrated sector sectors contributed approximately $61 million more than the workplace sector alone. The remaining $19 million reflects the difference between the broadcasting and telecommunications sectors and the truck transportation sector. The remaining 61 sectors account for the $148 million difference in the overall economic loss estimate, which is not statistically significant when comparing $4 billion to $3.8 billion. Based on Table 3.13 and Table 3.12, we conclude that workplace disruption is the most critical factor when assessing economic interoperability and the associated loss in the DIIM platform for the Houston MSA following Hurricane Harvey.

Table 3.13 results did not clarify the compositional balance between interconnected sectors and a single (workplace) sector. We want to take a fresh look at the dynamics. As a result, we reproduced Table 3.14 regarding the relative proportion of integrated versus single sector loss. Table 3.14's last column displays the modified results.

Table 3.14. Comparison between integrated and single sector disruption economic loss in proportions.

Integrated/Multi-sector Disruption (Economic Loss)			**Single Sector Disruption (Economic Loss)**		**Proportion=(Integrated/single)**
Top 10 Sectors	**Loss ($,000)**		**Top 10 Sectors**	**Loss ($,000)**	**Integrated/Workplace**
State and local general government	852,470		State and local general government	846,734	1.006774
Wholesale trade	389,753		Wholesale trade	**381,743**	1.020983
Miscellaneous professional, scientific, and technical services	258,121		Miscellaneous professional, scientific, and technical services	**250,713**	1.029548
Construction	158,465		Construction	**157,851**	1.00389
Insurance carriers and related activities	139,164		Insurance carriers and related activities	**134,317**	1.036086
Chemical products	130,930		Chemical products	**104,737**	1.250084
Federal general government (defense)	117,538		Federal general government (defense)	**116,991**	1.004676
Broadcasting and telecommunications	104,728		Truck transportation	**85,787**	1.220791
Computer systems design and related services	99,338		Computer systems design and related services	**96,862**	1.025562
Federal Reserve banks, credit intermediation, and related activities	96,133		Federal Reserve banks, credit intermediation, and related activities	**90,347**	1.064042
Total Loss (includes top 10 + remaining 61 sectors)	4,065,937		**Total Loss (includes top 10 + remaining 61 sectors)**	3,827,409	1.062321

Note. We reorganized the top ten list to compute the proportion. The colored sector is the non-match sector

Previously, state and local governments accounted for the most significant economic loss in Houston in terms of absolute difference. However, a closer examination of the relative proportion revealed that the combined influence of six disrupted sectors on state and local government is negligible. As a result, it reiterated that workplace disruption dominates the loss accounts of state and local governments. The chemical product industry, we discovered, experienced the most changes (25 percent). This 25% increase implies that the other six sectors contributed to the 25% increase in the loss of the chemical sector. As a result, those six industries (telecom, water, power, transportation, Internet, and retail) significantly impact chemical production. Except for workplace disruption, none of the other eight sectors demonstrated dominance in the six industries.

The only exception was the broadcasting and telecommunications sector, which showed a 22% increase over the transportation sector. The reasoning behind 22% is that the effect of workplace disruption is the same for both transportation and telecommunications. Nonetheless, the other six sector disruptions increased the loss in the broadcasting and telecommunications service by 22%. Finally, the difference in total sectoral loss between integrated and single sectors is only 6%, which is negligible. Individual sector averages in the top ten proportions are 1.066, slightly higher than the combined 71 sector average of 1.062. As a result, the top ten sectors' economic loss accounts for more than 90% of the total financial loss of 71 sectors.

3.6 Discussion and Policy Implication:

In this final chapter, we explored how the inoperability of the utility sector in Houston, Texas, leads to widespread sectoral GDP loss. Our DIIM model estimates a regional IO analysis of the top ten inoperable sectors and top ten sectors of economic loss. A closer look into these sectors reveals that most belonged to the service sectors. Hence, an inoperability in the manufacturing and service sector had different repercussions on Houston's economy, especially concerning job loss and GDP decline. Our result did not support pieces of evidence why such a pattern was observed in Houston, Texas.

A limitation of the DIIM model is that it did not go in-depth investigation into inoperability and loss. We acknowledge that because a comparison between agriculture vs. manufacturing or manufacturing vs. service sector could potentially unlock new dynamics. We plan to assess those comparative statics in an extension of this current project in a macro (Texas) and regional (Houston) level or similar regional setting at a different State level. If we find a similar pattern, we can conclude that service sectors are always sensitive to the spillover effect of inoperability.

We found that more than 90 percent of the inoperability in Houston is due to the workplace disruption in Post Hurricane Harvey. But our DIIM model falls short to account for whether this loss in the workplace is due to the proprietor income loss or loss of hourly wage workers. Because a proprietor can smooth its consumption despite the income loss, whereas failing to work for a few days means that a worker's lion's share of the income is lost due to the workplace and/or utility service interruption.

Again, we think the DIIM model may overestimate the inoperability and GDP loss. For example, oil and gas exploration is the leading manufacturing sector in Texas. Many of these production companies have their power generation and water supply line even though the DIIM model assumes uniform base inoperability, which may be different for the self-sufficient production of these gas and oil companies. We think this limitation opens up opportunities to update/extend the DIIM model so that we can estimate DIIM with and without these self-sufficient companies.

The issue is that policymakers may not be inclined to pay attention to infrastructure cost sharing and instead make it worse. To finance this generous tax deregulation and expand the electric grid, the Texas government imposes a cost to the consumer and working-class people, especially for making it resilient in the case of a hurricane. Taxpayers bear the burden of this expansion or deregulation of electricity providers. Our DIIM model estimation did not consider the imposition of cost to the taxpayers, which is a limitation of our findings. Whether the policymakers will pay attention to this concern in the future is a political question that the DIIM model cannot address.

3.7 Conclusion:

This paper estimated the inoperability and economic loss (DIIM) using the Dynamic Inoperability Input-Output Model. The DIIM was calculated by combining ORDER-CRISP household survey data from Texas in the aftermath of Hurricane Harvey. The survey data provided the duration of seven sectors' inoperability (electricity, water, telecommunications, Internet, transportation, workplace, and grocery). To estimate the DIIM results, we used the GUI platform module from the ORDER-CRISP project. The Bureau of Economic Analysis provided the Houston MSA GDP data (BEA). Then, using 71 BEA GDP sectors, we ran seven individual DIIM simulations. Finally, we ran seven sectors concurrently to achieve the general equilibrium of inoperability and economic loss. In Houston, Texas, our survey results identified the top ten inoperable sectors and the top ten economic loss sectors.

Our results indicated that 69% of the Houston respondents experienced electricity disruption, which created a city-wide repercussion effect on interdependent sectors, such as workplace water, transportation, Internet, and telecommunication. The integrated model of DIIM indicated that the total economic loss of the Houston area was $4.1 billion following the simultaneous inoperability of all the sectors. This loss estimate is similar to the result of $11.6 billion by Bhattacharyya et al. (2021)

The DIIM interface of our estimation provides meaningful guidance for disaster resilience and mitigation to policymakers at various levels. The advice includes providing a prioritized list of sectors most likely to be disrupted in the future due to a natural disaster. The top ten sectors of inoperability are (1) Food and beverage and tobacco products, (2) Construction, (3) State and local general government, (4) Management of companies and enterprises, (5) Other retail, (6) Wholesale trade, (7) Federal general government (defense), (8) Truck transportation, (9) Ambulatory health care services and (10) Administrative and support services.

Again, our DIIM estimation also generates a ranking of economic loss ($ 000), which are listed as (1) State and local general government, (2) Wholesale trade, (3) Miscellaneous professional, scientific, and technical services, (4) Construction, (5) Insurance carriers and related activities, (6) Chemical products, (7) Federal general government (defense), (8) Broadcasting and telecommunications, (9) Computer systems design and related services and (10) Federal Reserve banks, credit intermediation, and related activities. Based on the inoperability and loss rankings, we can deduce that disaster management in the state and local governments should be a top priority for policymakers because an effective and efficient local and state government can respond quickly and efficiently to disasters.

Finally, we compared workplace disruptions with the integrated disorder of seven sectors. Workplace disruption inoperable sectors are identical to that of the inoperable integrated industry. The economic loss of workplace disruption is $3.8 billion, whereas the integrated loss is $4.1 billion. When we compared the aggregate loss difference, we found that State and local government constitute the majority of the loss in both sectors. But when we converted the integrated loss as a proportion of workforce loss, we observed the chemical sector loss makes a difference to have slightly different aggregate loss numbers. Despite that, we think workplace disruption accounts for more than 90 percent of the economic loss in the Houston GDP following Hurricane Harvey.

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CHAPTER 4

CONCLUSION

4.1 Summary and Contribution of This Dissertation.

Natural disasters have increased in recent years due to climate and weather changes. As a result, people's lives, infrastructure, property, and livelihoods have been severely impacted. We need a better understanding of how natural disasters affect our communities at different layers, such as the country, state, and region. Policymakers can devise context-specific realistic approaches to combat such adverse events if they have a granular understanding of the impact on the affected locality, specific economic sectors, and the extent of damages and disruptions.

This dissertation focuses on quantifying and assessing the broader impact of catastrophic events. Chapter one evaluated whether media mentions of disaster events in the US newspaper impacted US development aid or crisis-dependent aid. We used aid data for 134 developing countries and media citations of different natural disasters in the US newspaper from 1966 to 2014. Our results showed that the development aid (ODA) disbursements had no connection to newspaper mentions. But country-specific news stories significantly affected food and humanitarian aid allocations. Our major contribution to the literature is that we introduced a unique categorized analysis of newspaper citations based on the most extensive sample. We introduced three new media variables to capture the media effect of aid.

Puerto Rico is a Caribbean Island and a US unincorporated territory located in the northeastern Caribbean Sea. During the 2017 hurricane season, two major hurricanes, Irma, and Maria, hit the island. The second chapter estimates Hurricane Maria's impact on the

Puerto Rican housing market, particularly given the island's vulnerability to hurricanes. We collected data from the Zillow website and built a comprehensive dataset of real estate transactions in Puerto Rico after Hurricane Maria. Then we conducted an empirical analysis to evaluate the post-Maria impact on the property market between 2018-2021. We demonstrated that home values significantly dropped and identified the major drivers affecting home values. This research is the first scientific study analyzing the housing market in Puerto Rico.

Houston, Texas, experienced prolonged disruptions when Hurricane Harvey landed in 2017. These disruptions caused multiplier effects on the interconnected sectors in the economy. For example, if people could not go to work because there was no electricity or transportation available. The socioeconomic consequence of such collateral disruptions is a massive loss of productivity, thereby losing a sizable portion of GDP. We estimated the economic loss due to these utility disruptions/intolerabilities in the third chapter.

We used a Dynamic Inoperability Input-Output Model (DIIM), a novel extension of the traditional Input-Output (IO) framework, to estimate the inoperability and economic loss. The DIIM was built on information collected through the ORDER-CRISP (Organizing Decentralized Resilience in Critical Interdependent-infrastructure Systems and Processes) household survey from Texas in the aftermath of Hurricane Harvey. The data provided the duration of inoperability in seven sectors (electricity, water, telecommunications, Internet, transportation, workplace, and grocery). To estimate the DIIM results, we used the GUI platform module from the ORDER-CRISP project. The Bureau of Economic Analysis (BEA) provided the Houston MSA GDP data. We ran seven sectors concurrently to achieve the general equilibrium of inoperability and estimate the economic loss. The analysis identified the top ten inoperable sectors and the top ten economic loss sectors in Houston, Texas.

Based on the survey data, most of Houston's respondents (69%) electricity disruption created a city-wide repercussion effect on other sectors, workplace water, transportation, Internet, and telecommunication. The integrated model of DIIM indicated that the total economic loss was $4.1 billion following the simultaneous inoperability of all interconnected sectors.

The DIIM interface guides disaster resilience and mitigation to policymakers at various levels. It provides a prioritized list of sectors that are likely to be disrupted in a similar natural disaster in the future. The top ten sectors of inoperability are (1) Food and beverage and tobacco products, (2) Construction, (3) State and local general government, (4) Management of companies and enterprises, (5) Other retail, (6) Wholesale trade, (7) Federal general government (defense), (8) Truck transportation, (9) Ambulatory health care services and (10) Administrative and support services.

Again, the DIIM estimation has also generated a ranking of economic loss ($000), which are listed as (1) State and local general government, (2) Wholesale trade, (3) Miscellaneous professional, scientific, and technical services, (4) Construction, (5) Insurance carriers and related activities, (6) Chemical products, (7) Federal general government (defense), (8) Broadcasting and telecommunications, (9) Computer systems design and related services and (10) Federal Reserve banks, credit intermediation, and related activities. Based on the inoperability and loss rankings, disaster management in the state and local governments should be a top priority for policymakers because a resilient local and state government can respond quickly and efficiently to disasters.

4.2 Conclusion and Scope of Future Research.

This dissertation covers a diverse research agenda of natural disasters. It sheds light on myth breakers at the US media-aid allocation nexus, the trend of losses in real estate values in Puerto Rico, and sectoral GDP loss in Houston, Texas, due to utility disruption and inoperability. The findings indicated that US aid allocation in response to disaster is limited to humanitarian and food aid. The results confirmed that home values in Puerto Rico experienced a significant loss in their value following the landfall of Hurricane Maria. Finally, Houston's estimated total economic loss was approximately $4 billion because of Hurricane Harvey’s devastation.

These findings unfold a new avenue of research. For example, lobbyist groups are vital for US foreign aid allocation decisions. Hence, future research can investigate the role of lobbyists and newspapers in the US humanitarian and food aid disbursement. For Puerto Rico, future research can address how creating improved building codes and standards can help reduce the impacts of future hurricanes and protect the property values. The inoperability analysis and economic loss estimates in Houston, Texas, can provide insights for policymakers to develop mechanisms to minimize the loss and improve hurricane resilience.

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