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hurricane damage mitigation efforts using forecast uncertainty**

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# How quickly can we adapt to change? An assessment of hurricane damage mitigation efforts using forecast uncertainty

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## Abstract

Our ability to adapt to extreme weather is increasingly relevant as the frequency and intensity of these events alters due to climate change. It is important to understand the effectiveness of adaptation given the uncertainty associated with future climate events. However, there has been little analysis of short-term adaptation efforts. We propose a novel approach of using errors from hurricane forecasts to evaluate short-term hurricane damage mitigation efforts. We construct a statistical model of damages for all hurricanes to strike the continental United States since 1955. While we allow for many possible drivers of damages, using model selection methods we find that a small subset explains most of the variation. We also find evidence supporting short-term adaptation effects prior to a hurricane landfall. Our results show that the 67 percent improvement in hurricane forecasts over the past 60 years is associated with damages being 16-63 percent lower than they otherwise would have been. Accounting for outlying observations narrows this range to 16-24 percent.

Keywords: Adaptation, Natural Disasters, Uncertainty

*JEL classifications:* C51, C52, Q51, Q54

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# 1 Introduction

Tropical cyclones, also commonly known as hurricanes or typhoons, are extremely powerful and destructive natural events that occur intermittently around the globe. They are amongst the most destructive and deadly climate disasters. Tropical cyclones account for six of the top ten costliest weather and climate disasters in the United States since 1980<sup>1</sup> and two of the top five costliest global natural disasters over the same period.<sup>2</sup>

Tropical cyclones are an intrinsic part of the climate system. Emanuel (2001, 2005a) illustrates the important role that they play in mixing different oceans layers to help distribute heat and energy. Large air-sea surface temperature differentials give rise to and help fuel tropical cyclones. There is also a link between the prevalence of greenhouse gases and tropical cyclones. Sobel et al. (2016) find that while aerosol cooling helps to limit hurricane intensity, warming from greenhouse gases increases the potential intensity of hurricanes. Thus, hurricanes both influence and are influenced by the climate; see Knutson et al. (2010).

It is important to understand the socioeconomic impact of hurricanes given their destructive nature and that both the frequency and intensity of these storms is closely tied to changes in the climate (see Burke et al., 2016). While there is a large literature on both the direct and the broader economic impact of hurricanes, there is mixed evidence for the effectiveness of medium- to long-term damage mitigation efforts. This is particularly true for the United States; see Hsiang and Narita (2012), Bakkensen and Mendelsohn (2016), and Davlasheridze et al. (2017).

We extend the literature by focusing on short-term damage mitigation. This includes temporary efforts to relocate vulnerable assets or minimize their damage. Short-horizon forecast errors are used to assess the effectiveness of these efforts. We construct a statistical model of hurricane damages for all hurricanes to strike the United States in the past 60 years that captures existing explanations for hurricane damages while allowing for additional determinants. The model is simplified using general-to-specific (GETS) methods to limit information loss. We find that a small subset of drivers explains much of the variation in hurricane damages. We also find evidence of short-term adaptation effects up to 12 hours prior to a hurricane landfall.

The paper is structured as follows: The next section explores drivers of hurricane damages. Section 3 explores the link between hurricane forecast errors and damages and how they can be used to identify short-term adaptation. Section 4 describes the data used, while section 5 explains the theoretical and statistical methods. Section 6 presents the results for the model of damages and compares its performance with existing models. Section 7 assesses whether short-term adaptation efforts are identified. Section 8 concludes.

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<sup>1</sup>Billion dollar events, NOAA

<sup>2</sup>MunichRe NatCatService

## 2 Determinants of Hurricane Damages

Extensive work exists on modeling the impact of hurricanes both in terms of damages and fatalities. While these studies span a broad literature, the determinants of hurricane impacts can roughly be broken down into three different categories: (1) natural and climate forces, (2) socioeconomic and demographic developments and (3) behavioral responses. This section examines each of these determinants and summarizes the previous findings.

Natural and climate forces are the main determinants of damages. Models of hurricane damages typically include maximum wind speeds as the primary driver of damages; see [Nordhaus \(2010\)](#), [Strobl \(2011\)](#), and [Murnane and Elsner \(2012\)](#). However, wind speed is an imperfect proxy of storm intensity. It suffers from measurement errors (see [Zhai and Jiang, 2014](#)) and is an insufficient proxy for damages due to storm surges and waves; see [Powell and Reinhold \(2007\)](#). An alternative measure of storm intensity is minimum central pressure, which is effectively an integral of wind speed over time making it is less susceptible to measurement error and providing a measure of storm strength; see [Chavas et al. \(2017\)](#).

Several studies examine the relationship between the climate / environment and hurricane damages. Some focus on geographical features of the strike location (see [Costanza et al., 2008](#), [Czajkowski et al., 2011](#)), while others focus on the impact of longer-term trends such as climate change or the ENSO cycle (e.g. [Emanuel, 2005b](#) and [Estrada et al., 2015](#)). They are generally interested in the drivers of storm intensity and how natural vulnerabilities influence damages.

Other determinants of damages are socioeconomic and demographic developments. These include changes in prices, populations, and incomes, as well as specific measures to mitigate losses. One of the first studies to systematically account for socioeconomic developments was [Pielke Jr and Landsea \(1998\)](#). They normalize hurricane damages using prices, population and capital stock. [Collins and Lowe \(2001\)](#) build on that framework by using local housing units instead of capital stock, while [Pielke Jr et al. \(2008\)](#) compare the two approaches. Others argue that normalizing by income is sufficient; see [Neumayer and Barthel \(2011\)](#). While these studies do not examine the effect of socioeconomic developments, they recognize that there is an association between these developments and damages.

The last major determinants of impacts are behavioral responses. While the literature associated with behavioral responses and impacts focuses primarily on fatalities and hurricane evacuation decisions, it is feasible that these issues could have a broader relevance to damages. The literature focuses on a multitude of factors with mixed results.<sup>3</sup>

More recently, the focus is on the link between socioeconomic developments and damages.

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<sup>3</sup>For example, see [Whitehead \(2003\)](#), [Solís et al. \(2010\)](#), [Jung et al. \(2014\)](#) and [Mozumder and Vásquez \(2015\)](#).

Specifically, there is an interest in medium- to long-term socioeconomic adaptation. This is captured either through incomes<sup>4</sup>, or through specific efforts such as building codes or mitigation expenditures; see [Dehring and Halek \(2013\)](#) and [Davlasheridze et al. \(2017\)](#). However, there has been no assessment of the effectiveness of short-term strategies.

Given the determinants of hurricane damages, the question that we seek to address is whether short-term adaptation efforts can mitigate damages. While it is not possible to directly observe these efforts, it is possible to proxy for them. In particular, we use forecast errors as a proxy to identify any effect. The use of forecast errors for identification has a rich history in economics. See in particular [Romer and Romer \(2004\)](#) and [Blanchard and Leigh \(2013\)](#). [Shrader \(2017\)](#) provides a recent example of how forecast errors can be used to identify adaptation to environmental risks. To ensure that we actually identify short-term adaptation efforts, it is necessary to discuss the links between forecast uncertainty and hurricane damages more broadly. The next section establishes a framework for these links.

### 3 Damages and forecast uncertainty, is there a link?

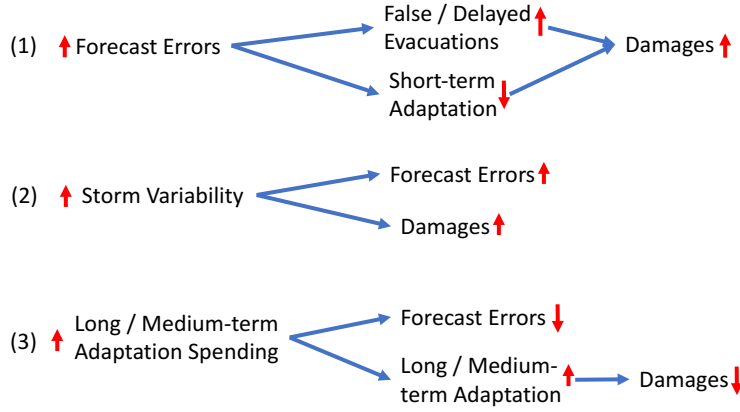
Past analyses of hurricane forecast uncertainty focus primarily on the link with evacuation decisions. However, some work has been done on the link with hurricane damages in the longer-term. [Letson et al. \(2007\)](#) identify a trade-off between improvements in medium-term (i.e. seasonal) forecasts and adaptation efforts. They argue that improved forecasts result in higher damages as people move into high risk locations due to a declining risk of fatalities. [Sadowski and Sutter \(2005\)](#) claim to test this relationship by showing that the declining lethality of hurricanes is correlated with an increase in hurricane damages.

We focus instead on the relationship between forecast errors and damages in the short-term. We allow for three channels through which this relationship may occur: (1) behavioral responses, (2) natural variability and (3) longer-term adaptation. [Figure 3.1](#) presents an overview of the channels. The rest of the section provides a description of these channels.

Behavioral decisions are the most studied link between forecast uncertainty and hurricane impacts. Uncertainty about the location and strength of the storm is associated with fewer people evacuating and results in higher casualties and costs; see [Baker \(1991\)](#) and [Lazo et al. \(2015\)](#). Higher uncertainty can also result in “false”, unnecessary, or delayed evacuations, which increases total costs; see [Regnier \(2008\)](#) and [Czajkowski \(2011\)](#). Forecast errors from previous storms may also impact behavioral decisions for future storms. However, there is little evidence to suggest this actually occurs; see [Dow and Cutter \(1998\)](#) and [Zhang et al. \(2007\)](#).

Given that forecast uncertainty is associated with hurricane evacuation decisions, it may also

<sup>4</sup>See [Kellenberg and Mobarak \(2008\)](#), [Bakkensen and Mendelsohn \(2016\)](#) and [Geiger et al. \(2016\)](#)



**Figure 3.1: Channels Linking Short-term Forecast Errors and Damages**

be linked with other behavioral decisions. Specifically, forecast uncertainty may be associated with efforts to mitigate storm damages. For example, the earlier households and businesses are notified about an incoming hurricane, the more likely they can mitigate damages before they evacuate. In the context of short-term forecasts that are up to five-days ahead, these measures could include boarding up windows, piling up sandbags and moving mobile assets out of the storm’s path. Although the impact of these measures is likely small, particularly for a direct hurricane strike, the fact that people undertake them suggests that there is some benefit. While there is no direct analysis of this link for hurricanes, support for this channel is found within the literature on damages from flooding; see [Carsell et al. \(2004\)](#).

Forecast uncertainty may also be indirectly associated with hurricane damages. Uncertainty could proxy for the natural variability of the storm. A storm that exhibits volatile characteristics may be difficult to forecast and for the same reasons cause more damage. However, in this sense, a poor forecast does not relate directly to higher damages. For example, the rapid intensification of a hurricane just prior to landfall is difficult to forecast and is also associated with increased damages; see [Elsberry et al. \(2007\)](#) and [Kaplan et al. \(2010\)](#). Furthermore, a slow moving storm results in higher overall rainfall and therefore increased flooding and damages and can also be forecast poorly.<sup>5</sup> For example, Harvey [2017] experienced rapid intensification in its initial buildup and then became slow moving once it made landfall. In either case, changes in storm dynamics are associated with increased forecast errors and higher damages. Thus, the relationship between forecast errors and damages is moderated by changes in the storm’s dynamics. These dynamics need to be controlled for in order to assess whether there is a direct link between forecast uncertainty and damages.

Another potential indirect link is through spending to mitigate hurricane damages. Adaptation efforts often go hand-in-hand with efforts to improve hurricane forecasts. The effectiveness

<sup>5</sup>Forecasts of hurricane rainfall often rely on hurricane track forecasts. See [Kidder et al. \(2005\)](#).

of longer-term damage mitigation efforts could therefore be correlated with improved forecasts. The operation of this channel relies on the simultaneous gradual improvement of forecasts as well as increased adaptation expenditures. In order to control for this channel, longer-term adaptation efforts need to be accounted for.

Our aim is to assess the existence of a (direct or indirect) link between hurricane damages and short-term forecast uncertainty. Once existence is established, then we can identify whether the short-term adaptation channel is operative. We first develop a statistical model of hurricane damages through which any forecast uncertainty channel can operate. The next section describes the data before the methods and results are discussed.

## 4 Data

We examine the impact of hurricanes in the Atlantic basin of the continental United States of America. While data on U.S. hurricane strikes dates back to the 1850's, we focus on hurricane strikes since 1955 for which a continuous database of hurricane forecasts exists. This section describes the number of hurricanes included in the analysis. Section 4.2 then describes the hurricane damage data used and how it compares with other commonly used sources. Section 4.3 describes which forecasts are used, where they are from and how the forecast errors are computed. The rest of the section describes additional variables used in the analysis.

### 4.1 Land-falling Hurricanes and Strikes

The hurricane research division of the U.S. National Oceanic and Atmospheric Administration (NOAA) maintains a list of every storm with hurricane force winds to make landfall in the continental United States since 1851. 192 Atlantic hurricanes struck the U.S. between 1900 and 2015.<sup>6</sup> Of these strikes, 88 occurred between 1955 and 2015. Accounting for the fact that some hurricanes struck in multiple locations, i.e. Katrina [2005] first struck the Florida panhandle and then moved into the Gulf and struck Louisiana several days later, there were 101 hurricane strikes between 1955 and 2015.

### 4.2 Hurricane Damages

Hurricane damages have been extensively studied for all U.S. land-falling hurricanes since 1900. Pielke Jr and Landsea (1998) was one of the first studies to compile comprehensive data on hurricane damages since 1900. Their analysis draws on estimates from annual publications of hurricane season reports which also contain data on fatalities and storm characteristics. Pielke Jr et al. (2008) updated and extended that dataset through 2005.

<sup>6</sup>Note that the hurricane research division actually maintains two lists of all continental hurricane land-falls (see [http://www.aoml.noaa.gov/hrd/hurdat/All\\_U.S.\\_Hurricanes.html](http://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html) and <http://www.aoml.noaa.gov/hrd/tcfaq/E23.html>, last accessed July 2017). The former list is used here since it is based on the most up-to-date data. Since 1955, the only difference is that the former list includes Helene [1958] and Ophelia [2005] but excludes Diane [1955].

Since then, additional hurricane damage datasets were established. The ICAT dataset is one of the more popular, which draws from the same underlying sources as [Pielke Jr et al. \(2008\)](#) and contains damage estimates for all hurricanes from 1963-2012. Another popular database is Munich RE’s NatCatSERVICE, which provides damage estimates for all hurricanes from 1980-2012. The SHELDUS database is another source for hurricane damages. It draws from NOAA’s Storm Events database, which documents the costs and fatalities associated with each storm event in each county in the U.S. since 1959.<sup>7</sup> Following work by [Smith and Katz \(2013\)](#), who found that previous estimates tend to underestimate the most damaging storms, NOAA generated a list of the damage and fatalities associated with weather and climate disasters that did at least a billion dollars in damage since 1980.<sup>8</sup> Thus, there is no shortage of information on direct hurricane damages.<sup>9</sup>

The difficulty associated with using many of these sources is that they do not extend all the way back to 1955 nor do they represent the most up-to-date estimates of hurricane damages. Furthermore, given that we treat each of the individual strikes associated with a given hurricane separately, most of the prior datasets are not directly useful. As a result, we build our own dataset of direct hurricane strike damages since 1955.

Damage estimates are collated for each strike using multiple sources. The primary historical source follows the approach by [Pielke Jr et al. \(2008\)](#) and ICAT in using the annual Atlantic Hurricane Season reports (1955-2015).<sup>10</sup> This was supplemented and updated with up-to-date data from individual tropical cyclone reports (1955-2015).<sup>11</sup> The data was updated using the most recent data on the costliest storms provided by NOAA’s hurricane research division.<sup>12</sup>

The resulting dataset on hurricane damages is generally comparable to previous datasets. Table 4.1 provides comparisons across various data sources. The current dataset is closest to [Pielke Jr et al. \(2008\)](#) and ICAT’s datasets due to similarities in how they were constructed. However, there are some important differences. Several hurricanes, notably Celia [1970], had their damage estimates revised upwards. Furthermore, there are some hurricanes for which the damages are lower than previously reported. For example, Agnes [1972] initially struck Florida as a hurricane. It then weakened and later re-intensified into a tropical storm and caused substantial damage in Pennsylvania, New Jersey and New York. The current dataset focuses exclusively on damages associated with the initial hurricane strike.

<sup>7</sup>SHELDUS is available by subscription only. However, the Storm Events database is publicly available.

<sup>8</sup>Also known as the Billion dollar events database.

<sup>9</sup>See [Deryugina \(2017\)](#) for an attempt to assess indirect damages.

<sup>10</sup>The reports were published in the Monthly Weather Review through 2011 and are available from the Hurricane Research Division until 2011. The NHC maintains the annual summaries since 2012.

<sup>11</sup>Historical reports are available from the National Hurricane Center from 1958-2016 and NOAA from 1954-2005.

<sup>12</sup>See [Blake et al. \(2011\)](#).



	Source	Obs	Median		Std. Dev.		Min		Max		Corr.	Similar
			dif	(%)	dif	(%)	dif	(%)	dif	(%)	(%)	(%)
Pielke Jr and Landsea (1998)		52	-	-	304	27.69	-2,142	-95.24	141	100.00	99.68	84.62
Pielke Jr et al. (2008)		79	-	-	3,105	321.70	-27,000	-95.24	1,530	2,185.71	99.48	70.89
	ICAT	86	-	-	3,950	52.25	-27,000	-95.24	159	387.73	99.46	68.60
	Storm Events	83	-26	-27.15	9,865	45.29	-74,400	-95.83	4,040	180.00	91.32	16.87
	Billion Events (BE)	28	287	4.00	4,149	28.23	-6,400	-31.93	17,000	117.00	98.85	7.14
	-BE (Low)	28	-760	-13.98	5,240	25.41	-21,700	-53.33	7,000	73.60	98.86	0.00
	-BE (High)	28	1,147	19.02	8,187	34.53	-1,200	-12.49	42,800	164.01	98.72	0.00

Note: All external datasets are expressed relative to the current dataset. Dif is calculated by taking the external damage estimate and subtracting the current damage estimate. The figures are in nominal millions of U.S. dollars. % dif is computed by dividing dif by the current damage estimate to get a percentage difference. Thus, a positive number implies that the external source had a higher estimate, whereas a negative number implies that the current damage estimate is higher. Corr represents the correlation between the current data source and the external data. Similar represents the share of observations for which differences between the current and the external damage estimates are less than \$1 million.

**Table 4.1: Comparing Hurricane Damage Data Sources**

The current dataset is also in a broad sense comparable with the estimated damages from the Storm Events database and Billion dollar events database. However, damages tend to be considerably higher than in the Storm Events database (due to under-reporting) and are lower than those reported in the Billion dollar events database. Note that while the damages are often lower than those in the Billion dollar event database, they typically fall within the upper and lower confidence intervals.

### 4.3 Hurricane Forecasts, Actuals and Errors

There is a long history of hurricane forecasting in the United States. Hurricane forecasts have been provided by the U.S. government since the 1850's; see [Sheets \(1990\)](#) for a historical perspective. Despite this long history, forecasts are only available going back 60 years. The National Hurricane Center maintains a forecast database since 1954 through the automated tropical cyclone forecasting system (ATCF). This system provides an archive of tropical cyclones forecasts as well as the actual tracks and storm advisories.

For any given storm there are several forecast measures available. Forecasts are produced for the track of the hurricane (latitude and longitude), maximum sustained wind speed, central pressure and wind radii ranging from 6-120 hours-ahead. Despite this apparent abundance, only forecasts of the hurricane track are consistently available since 1955. Maximum wind speed forecasts are available since 1990, whereas forecasts of central pressure are sporadically available for a handful of hurricanes. Furthermore, forecast horizons only extended out to 24-hours ahead until 1967 at which point they were extended out to 72-hours ahead (3 days). The forecast horizon was extended to 120-hours ahead (5 days) in 2001.

Many different forecasts are available. For example, the ATCF system has 128 different forecasts for hurricane Matthew [2016]. However, this is not true for all hurricanes. Six methods are available for Celia [1970] while only two methods are available for all hurricanes prior to

1970. These methods span from simple persistence and climatology forecasts to multi-level global ensemble models.

We use the “official” NHC forecast since it is deeply integrated with the emergency warning system and is widely distributed to and used by news stations. The “official” forecast is not specifically defined in terms of a single model and should not be considered the same across all hurricanes. Its performance has changed dramatically with the advent of new methods and technologies, particularly through the use of satellite technology. See [Shuman \(1989\)](#), [Sheets \(1990\)](#) and [Rappaport et al. \(2009\)](#) for a historical overview of how weather and hurricane forecasts have changed over the past 60 years.

While forecasts are generally available at 6-hour intervals across the entire life of the storm, they are not all necessarily relevant to the impact of the hurricane. This is especially true when some hurricanes are active for over a month and transverse the entire Atlantic ocean. In order to focus only on those forecasts that are most likely to be associated with the impact of the hurricane, forecasts are re-labeled in terms of X-hours before landfall.

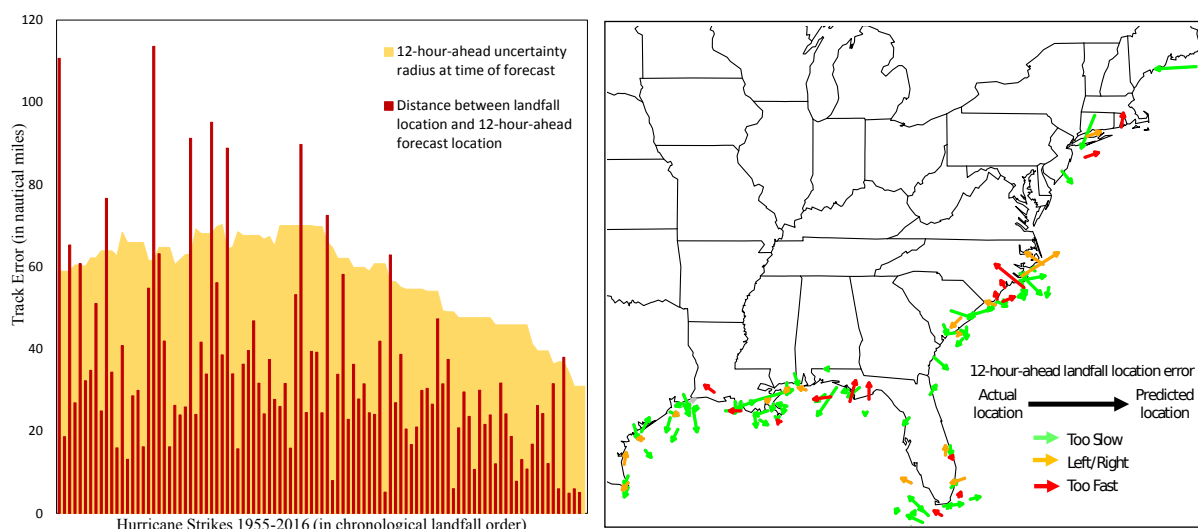
The timing of the hurricane landfall is rounded to the closest point in a 6 hour window. This simplification is necessary since forecasts and observations are generally only available at 6 hour intervals. Thus, if a hurricane made landfall at 16:00 UTC then the closest observation/forecast to that point is 18:00 UTC. Then, 12 hours are subtracted from the landfall time to get the time that the 12-hour-ahead landfall hurricane forecast for a given storm was generated (i.e 06:00 UTC). Subtracting an additional 12 hours gives the time at which the 24-hour-ahead landfall hurricane forecast was generated (i.e. 18:00 UTC the previous day). This step is repeated back to the 120-hour-ahead landfall hurricane forecast.

We focus on the 12-hour-ahead landfall forecasts because they are available for most hurricane strikes.<sup>13</sup> Longer horizons are not always available either because the storm had a short pre-strike lifespan or because they were not yet produced in that year. Thus, longer horizons are used to assess the robustness of the relationship.

The actual track for a given hurricane is also stored within ATCF and represents the best estimate of the hurricane. These actual values are more commonly known as being part of the hurricane database (HURDAT), which has data on hurricanes going back to 1851. NOAA’s Hurricane Research Division (HRD) also maintains a database of best track estimates and re-analyses of hurricanes (known as HURDAT2). While data from both sources is available for all hurricanes in the sample, we use HURDAT2 since it is the most up-to-date source.<sup>14</sup>

<sup>13</sup>The ATCF system does not have forecasts for all landfalling hurricanes from 1955-2015. In particular, forecasts are not available for Debra [1959] and Ethel [1960], which is likely due to their short duration.

<sup>14</sup>For the purposes of our analysis, both sources are effectively identical.



Panel A: 12-hour-ahead landfall errors over time

Panel B: Direction of 12-hour-ahead landfall errors in space

Note: Errors are computed using [Vincenty \(1975\)](#) formula for the distance between two points on the surface of a spheroid. The 12-hour-ahead landfall errors are computed such that the forecast was made 12 hours before the closest observed point of the hurricane at landfall. The shaded area is the implied cone of uncertainty which is computed so that two-thirds of historical official forecast errors over a five-year sample prior to the strike fall within the area. In panel B, the coloring of arrows is based on the calculated angle of the triangle which is calculated from the distance between the forecast and the actual (A: shown), the distance between the actual 12-hour prior and the current actual (B) and the distance between the 12-hour prior actual and the forecast (C), where the angle of interest is opposite of C. Green is less than 90 degrees, orange is greater than 90 but less than 135 degrees and red is greater than 135 degrees.

**Figure 4.1: 12-Hour-Ahead Hurricane Landfall Track Errors**

Hurricane track forecast errors are computed differently from typical forecast errors. Given the curvature of the earth, track forecast errors are calculated using [Vincenty \(1975\)](#)'s formula for the distance between two points on the surface of a spheroid.<sup>15</sup> As a result, the track forecast error does not contain any directional interpretation but is purely a distance measure (i.e. it is akin to an absolute forecast error). Panel A of Figure 4.1 illustrates that the forecast errors have declined on average by about 60 percent over the whole sample. Over the same period the implied a-priori forecast uncertainty has also declined so that both the errors and the expected uncertainty associated with the forecasts has declined.<sup>16</sup>

Not all error directions have the same theoretical relationship with damages. Forecasts that are too slow or biased to either side of the landfall location are interpretable as providing less warning time for people in the impacted areas. On the other hand, forecasts that are too fast could underestimate the amount of rainfall and flooding and make people less likely to prepare for flood damages. Thus, despite having different interpretations, all forecast error directions can be linked to damages through the short-term adaptation channel.

One way to assess the direction of forecast errors is to plot the forecasts and the actual hurricane locations at the time of landfall. Panel B of Figure 4.1 plots the hurricane locations,

<sup>15</sup>This approach is considered to be more accurate than the great-circle distance.

<sup>16</sup>The results in section 6 are robust to the inclusion of the a-priori cone of uncertainty (not shown).

12-hour track forecasts and the difference between them for the closest available points to each hurricane strike, where the base of the arrow is the actual hurricane location and the head of the arrow is the projected location. The coloring is based on the size of the angle in terms of where the hurricane is coming from, where it actually is and where it was forecast to be with green indicating a faster than expected hurricane and red a slower than expected hurricane. Overall, there is a greater number of faster than expected hurricanes.<sup>17</sup>

#### 4.4 Other Variables

While the focus is on the relationship between forecast errors and hurricane damages, other determinants are included; see section 2. We include both variables that have and have not been used in previous analyses. The inclusion of these variables allows us to simultaneously assess the importance of alternative channels while also controlling for important determinants.

The first set of variables is the natural and climate forces category. This includes: maximum sustained wind speed, central pressure, accumulated cyclone energy, maximum rainfall, maximum surge height, maximum hurricane category, global mean surface air temperature, soil moisture, and historical hurricane frequency. Other potentially relevant variables, such as the storm power dissipation index (see Emanuel, 2011) and wetland areas (see Costanza et al., 2008), are excluded due to data availability. See Appendix Table A.1 for specific definitions, sources, and summary statistics for these and all other variables used.

The second set of variables falls within the socioeconomic / demographic vulnerabilities channel. These include income per capita, population density, income density, housing density and income per housing unit. Following Strobl (2011), we use county level population and personal income estimates which are available from the Bureau of Economic Analysis (BEA) since 1969. Prior to 1969 county level population estimates from the U.S. Census, which are available every 10 years going back to 1950, are used as well as state level population and personal income estimates going back to 1950 at an annual basis from the BEA. Annual county level population values prior to 1969 are computed by interpolating county level population shares between decades and then distributing using state level data.<sup>18</sup>

Annual county level personal income data prior to 1969 is computed as follows. First, we assume that county level personal income shares remain at their 1969 levels going back to 1955. Second, we estimate annual income shares using a simple fixed effects panel data model and then back-cast the income shares starting in 1969.<sup>19</sup> In both cases, the county level shares

<sup>17</sup>Robustness checks (not shown) indicate that the results are unchanged after controlling for the size of the angle. However, the angle is positively associated with damages (not significant) suggesting that storms which move slower than expected may be more damaging.

<sup>18</sup>A similar approach was used by Pielke Jr et al. (2008)

<sup>19</sup>The panel data model was estimated over for all U.S. counties from 1969 to 1999 using leads of income and population shares as explanatory variables.

are then combined with state level income to get a county level measure. The two measures are averaged to produce a more robust measure of income. The data on county level land area and housing units comes from the U.S. Census going back to 1950 where the values are linearly interpolated between census estimates.<sup>20</sup> The analysis excludes potentially important determinants of socioeconomic vulnerabilities such as building codes; see [Dehring and Halek, 2013](#). However, longer-term adaptation measures such as FEMA’s Community Rating System and mitigation expenditures (see [Davlasheridze et al., 2017](#)) are included for robustness.

The final set of variables are those that fall within the behavioral responses channel. The variables included are an index of the masculinity and femininity of Hurricane names from [Jung et al. \(2014\)](#), and hurricane warnings as a proxy for hurricane evacuations (see Appendix B.1 for a description).<sup>21</sup> Other potentially important behavioral variables such as the proportion of people that evacuated are excluded due to data limitations.

Several fixed effects dummy variables are included to help control for the potentially important concerns. This includes a simple annual linear trend, a time dummy to control for the six-hour period in which a storm makes landfall, a monthly dummy to control for different monthly affects and a state dummy to control for possible differences across U. S. states. Individual storm dummies are included to assess the stability of the model.

## 5 Methods

We generalize the theoretical approach used in [Bakkensen and Mendelsohn \(2016\)](#) and others. As described in section 2 above, potential hurricane impacts  $I_{i,t}$  (i.e. damages) depend on (1) natural/climate forces, (2) socioeconomic vulnerabilities and (3) behavioral responses so a given hurricane impact is determined by some combination of these factors

$$I_{i,t} = g(V_{i,t}, F_{i,t}, R_{i,t}), \quad (5.1)$$

where  $V_{i,t}$  represents a vector of societal vulnerabilities,  $F_{i,t}$  is a vector of natural/climate forces, and  $R_{i,t}$  represents a vector of behavioral responses for a given storm  $i$  at time period  $t$ . A simple theoretical approach is to use the Cobb-Douglas form for  $g()$  so that

$$I_{i,t} = AV_{i,t}^\alpha F_{i,t}^\beta R_{i,t}^\gamma, \quad (5.2)$$

where  $A$  is a fixed constant that has no inherent interpretation in the current context. This potential impact function be adapted further given that hurricane damages approximately follow a log-normal distribution; see [Willoughby \(2012\)](#), [Blackwell \(2014\)](#) and Appendix Figure A.1.

<sup>20</sup>This follows the approach from [Collins and Lowe \(2001\)](#). Note that counties are aggregated following BEA modifications to U.S. Census codes: <https://www.bea.gov/regional/pdf/FIPSMODIFICATIONS.pdf>. Last accessed November 2016.

<sup>21</sup>Note that hurricane warnings are ultimately excluded from the model due to missing observations. However, the overall results remain similar when it is included.

Taking logs of equation (5.2) gives the following log-linear expression

$$\ln(I_{i,t}) = \ln(A) + \alpha * \ln(V_{i,t}) + \beta * \ln(F_{i,t}) + \gamma * \ln(R_{i,t}), \quad (5.3)$$

where the coefficients can now be interpreted in percentage terms. Given that the damages approximate a log-normal distribution, it is sufficient to use a standard OLS regression analysis.

Many studies implicitly utilize this theoretical formulation. Emanuel (2005b), Nordhaus (2010) and Strobl (2011) set  $\gamma \equiv 0$  and  $\alpha \equiv 1$  to examine the relationship between damages and natural forces. Others implicitly set  $\gamma \equiv 0$  to investigate the relationship between damages and socioeconomic vulnerability; see Kellenberg and Mobarak (2008), Bakkensen (2013), Bakkensen and Mendelsohn (2016) and Geiger et al. (2016).

Our methodological framework is less restrictive. To build a model of hurricane damages, we expand on previous explanations and theory. We use the notion of 'model encompassing' to develop a sufficiently general model that either explains or incorporates previous findings. This approach is broadly defined as a general-to-specific (GETS) modeling framework.

The GETS modeling framework is thoroughly described in Campos et al. (2005). Recent developments, discussed by Hendry et al. (2008), Doornik (2009), Hendry and Doornik (2014) and Hendry and Johansen (2015), illustrate the usefulness of the GETS framework to a wide class of applications. Given that previous studies focus on individual determinants of damages, the GETS approach is a nice way to simultaneously summarize and extend the literature.

The GETS framework can be described in the current context as follows. First, a general unrestricted model (GUM), which includes all potentially relevant determinants of hurricane damages, is specified. Second, the GUM is simplified so that the final model exhibits minimal information loss based on user-specified target values. Third, the model reduction is done such that multiple paths are followed to limit any path dependency in the process. Finally, the selected model provides a parsimonious explanation of the GUM while also ensuring that it satisfies some basic diagnostic tests. See Doornik (2009) for a detailed description.

When multiple models are retained which satisfy all of these criteria, information criteria are used to select between equally valid models. Alternatively "thick modeling", as proposed by Granger and Jeon (2004) and discussed in the GETS context by Castle (2017), can be used to pool across models. In either case, the goodness of fit is not considered. These approaches perform best when the GUM is statistically well specified and nests the underlying local data generating process. Thus, formulation of the GUM is an integral part of the process.

The GUM includes all of the major determinants (natural forces, socioeconomic vulnerabilities, behavioral responses, and forecast uncertainties) as well a variety of dummy variables to control for spatial and temporal heterogeneity. As a result, the GUM contains 47 explanatory

variables over the full sample of 98 observations:

$$\begin{aligned}
\text{damage}_i = & \alpha_0 + \alpha_1 \text{pd}_i + \alpha_2 \text{hd}_i + \alpha_3 \text{ih}_i + \alpha_4 \text{ip}_i + \alpha_5 \text{FREQ}_i \\
& + \beta_1 \text{rain}_i + \beta_2 \text{surge}_i + \beta_3 \text{npress}_i + \beta_4 \text{wind}_i + \beta_5 \text{MOIST}_i + \beta_6 \text{CAT}_i \\
& + \beta_7 \text{ace}_i + \beta_8 \text{GST}_i + \gamma_1 \text{forc12}_i + \gamma_2 \text{MASFEM}_i \\
& + \delta_1 \text{YRTREND}_i + \delta_2 \text{STKTREND}_i + \eta \text{HOUR}_i + \kappa \text{MONTH}_i + \lambda \text{STATE}_i,
\end{aligned} \tag{5.4}$$

where lowercase variables are logarithms.

The first line of equation (5.4) lists the potential determinants of socioeconomic vulnerability: population density (pd), housing unit density (hd), income per housing unit (ih), income per capita (ip), and historical hurricane frequency in the strike location (FREQ) as a proxy for longer-term adaptation. The second and (part of the) third lines include potential natural forces: maximum rainfall (rain), storm surge (surge), negative minimum pressure (npress), maximum wind speed (wind), soil moisture relative to trend (MOIST), maximum hurricane category (CAT), accumulated cyclone energy (ace) and global surface temperature (GST). The last part of the third line includes forecast uncertainties: 12-hour-ahead forecast track errors (forc12), and behavioral responses: femininity of hurricane name (MASFEM). Finally, the last line includes all of the spatial and temporal controls. See Appendix Table A.1 and Figure A.2 for descriptions of the variables, their sources, summary statistics, and plots.

## 6 Results

This section presents the results and interpretation of the initial analysis where the GUM is estimated and then reduced. Equation (5.4) represents the general formulation of the hurricane damage model that is estimated. The GUM has 48 parameters (i.e. 47 variables plus the variance). The model reduction occurs in such a way that variables are removed up until a predetermined target value, which determines the false-retention rate of variables in expectation. The target value is typically set based on the number of variables being selected over so that *on average* a single irrelevant variable is kept in the final model. Given that all variables are selected over, the target value here is set to equal  $\frac{1}{48} \approx 0.02$ . We also adjust the target value to ascertain how sensitive the results are to this specification.

Table 6.1 presents the selected models using target values ranging from 1 – 5 percent. Although the selected models are almost identical, that masks a large degree of underlying uncertainty. The uncertainty is illustrated by the number of terminal models for each selected model which range from 12 – 14 and is in large part due to almost perfect collinearity between the population, income and housing variables (see Appendix Figure A.3). Although each terminal model represents a valid reduction of the GUM based on the target critical value, the final se-



lected model is chosen based on the Schwarz information criterion.<sup>22</sup> Thus, the selected models should be viewed as belonging to a sample of potentially valid models.

Table 6.1 shows that hurricane damages are positively associated with housing/population and income as well as with (-) central pressure, rainfall, storm surge, and the 12-hour-ahead track forecast errors. Income per housing unit, minimum central pressure, max rainfall, max storm surge, and the forecast errors are all retained across alternative target values. This indicates that the t-ratios of these variables are so high that they are selected regardless of the target value. The selected models alternate between housing and population density, which is not surprising since they are almost perfectly correlated. However, the parameter estimates for the other variables do not change much across these two specifications.

	(1)	(2)	(3)	(4)	(5)
Selection target:	1%	2%	3%	4%	5%
# Terminal Models	13	12	12	14	12
population density		0.399*** (0.142)	0.399*** (0.142)		
housing density	0.404*** (0.149)			0.404*** (0.149)	0.404*** (0.149)
income per housing unit	1.284*** (0.175)	1.330*** (0.163)	1.330*** (0.163)	1.284*** (0.175)	1.284*** (0.175)
min central pressure (-)	51.975*** (8.433)	52.036*** (8.405)	52.036*** (8.405)	51.975*** (8.433)	51.975*** (8.433)
max rainfall	1.140*** (0.310)	1.098*** (0.310)	1.098*** (0.310)	1.140*** (0.310)	1.140*** (0.310)
max storm surge	1.344*** (0.374)	1.301*** (0.374)	1.301*** (0.374)	1.344*** (0.374)	1.344*** (0.374)
12-hour forecast error	0.478** (0.233)	0.465** (0.233)	0.465** (0.233)	0.478** (0.233)	0.478** (0.233)
$\hat{\sigma}$	1.261	1.257	1.257	1.261	1.261
$R^2$	0.821	0.822	0.822	0.821	0.821
$F_{AR(2)}$	0.244	0.356	0.356	0.244	0.244
$F_{ARCH(1)}$	0.845	1.291	1.291	0.845	0.845
$\chi^2_{nd}(2)$	8.344**	7.959**	7.959**	8.344**	8.344**
$F_{Het}$	1.760*	1.787*	1.787*	1.760*	1.760*
$F_{Het-X}$	1.020	1.125	1.125	1.020	1.020
$F_{RESET23}$	1.296	1.579	1.579	1.296	1.296
*p< 0.1 **p< 0.05 ***p< 0.01					

Notes: All equations are estimated using 98 observations and include a constant and dummy variables for Gerda [1969] and Floyd [1987]. The standard errors are in parentheses. Selection target refers to the target value (target size) at which model selection occurs.

**Table 6.1: Baseline Models of Hurricane Damages**

The selected models are aligned with the “Final GUM” and the “thick modeling” approach; see Appendix Table A.2. The results are also broadly unchanged in alternative model selection specifications where highly co-linear variables (i.e. housing density or population density) are

<sup>22</sup>Note that the results are fairly consistent when the Hannan Quinn or Akaike information criteria are used.



either forced into or excluded from the GUM. For example, if housing density and income per household are forced into the GUM then the results are identical across target values and the number of terminal models never exceeds 8.<sup>23</sup>

Interpretation of the coefficients and their significance requires that the underlying assumptions about the model are satisfied. Therefore, it is useful to examine a battery of diagnostic tests. The diagnostic tests shown in Table 6.1 are: the  $F_{AR(2)}$  test for residual autocorrelation (see Godfrey, 1978), the  $F_{ARCH(1)}$  test for time varying variances (see Engle, 1982), the  $\chi^2_{nd}(2)$  test for non-Normality (see Doornik and Hansen, 2008), the  $F_{Het} / F_{Het-X}$  test for residual heteroskedasticity (with and without cross products, see White, 1980), and the  $F_{RESET23}$  test for incorrect model specification (see Ramsey, 1969).

A rejection of the null hypothesis suggests that the assumption associated with that test is invalid. The results of the diagnostic tests indicate the null hypothesis that the model residuals are normally distributed, is rejected at a 5% critical value. There is also evidence of heteroskedasticity in the residuals.

This misspecification can be dealt with by extending the model. First, by allowing for potential outliers which may induce non-normality. Second, adding squares of the explanatory variables can help capture heteroskedasticity in the residuals. Rather than re-selecting the entire model again, it is possible to add onto the current model; see Hendry and Johansen (2015). The results of (1) from Table 6.1 is treated as the “baseline” which is embedded within a more general model that includes impulses for every observation and squares of the variables.<sup>24</sup> When model selection occurs, the “baseline” is forced into the GUM so that it is always retained along with any relevant outliers or squared terms. This allows us to assess the robustness of the results while also improving the underlying model.

Table 6.2 presents the results. Column (1) is the “baseline” and is identical to Table 6.1 column (1). Column (2) is the baseline plus large outliers. Column (3) presents the results for impulse indicator saturation (IIS), whereby a dummy variable is included for every observation, exploiting the software’s ability to examine multiple block path searches, and then select; see Hendry et al. (2008). Column (4) presents selection over the squares of the variables. Column (5) presents the results for when IIS and selection are done simultaneously. In all cases the “baseline” is not selected over and a 1% target value is used.<sup>25</sup>

The results in Table 6.2 present a fairly consistent picture. Even when accounting for outliers, the model parameters remain fairly stable, albeit with a slight downward drift in some of the

<sup>23</sup>Results available upon request.

<sup>24</sup>We focus here on the model with housing density. However, similar results are obtained for population density.

<sup>25</sup>The results for column (4) remain the same even if the selection target is 0.5%.

	(1) Base	(2) Outliers	(3) IIS	(4) Squares	(5) IIS+Squares
housing density	0.404*** (0.149)	0.386*** (0.141)	0.417*** (0.121)	0.360*** (0.143)	0.292*** (0.103)
income per housing unit	1.284*** (0.175)	1.270*** (0.166)	1.185*** (0.144)	1.492*** (0.181)	1.400*** (0.128)
income per housing unit sq.				0.398*** (0.130)	0.448*** (0.089)
min central pressure (-)	51.975*** (8.433)	52.924*** (7.981)	53.401*** (6.860)	49.713*** (8.098)	55.470*** (5.662)
max rainfall	1.140*** (0.310)	1.113*** (0.294)	0.810*** (0.256)	0.930*** (0.305)	0.518*** (0.213)
max storm surge	1.344*** (0.374)	1.240*** (0.355)	0.929*** (0.309)	1.390*** (0.358)	0.932*** (0.251)
12-hour forecast error	0.478** (0.233)	0.543** (0.222)	0.246 (0.200)	0.517** (0.224)	0.298* (0.162)
Outlying storms:					
Helene [1958]					-2.695*** (0.860)
Cindy [1959]			-3.818*** (1.060)		-4.219*** (0.856)
Gracie [1959]					-2.725*** (0.837)
Alma [1] [1966]		-4.130*** (1.219)	-4.277*** (1.040)		-4.405*** (0.835)
Bret [1999]					-2.478*** (0.867)
Alex [2004]			-3.537*** (1.039)		-3.560*** (0.834)
Arthur [2014]			-4.079*** (1.099)		-4.170*** (0.883)
$\hat{\sigma}$	1.261	1.192	1.017	1.206	0.816
$R^2$	0.821	0.842	0.889	0.838	0.932
$F_{AR(2)}$	0.244	0.546	0.409	0.299	0.833
$F_{ARCH(1)}$	0.845	4.886**	0.032	1.088	2.136
$\chi^2_{nd}(2)$	8.344**	6.347**	1.607	15.268***	0.907
$F_{Het}$	1.760*	1.709*	1.469	1.129	0.878
$F_{Het-X}$	1.020	1.295	1.299	0.995	0.969
$F_{RESET23}$	1.296	1.277	7.601***	0.663	1.350
*p< 0.1 **p< 0.05 ***p< 0.01					

Notes: All equations are estimated using 98 observations and include a constant and dummy variables for Gerda [1969] and Floyd [1987]. The standard errors are in parentheses. The selection target is 1% for columns (2)-(5). All variables are demeaned to facilitate interpretability of the coefficients.

**Table 6.2: Robust Models of Hurricane Damages**

coefficients. The diagnostic tests do not indicate any issues with the model when both the outliers and non-linearity are accounted for in column (5). This is therefore a “robust” model from which it is possible to interpret the estimated parameters. See Appendix C for an in- and out-of-sample assessment of the fit of this model.

## 6.1 Interpreting the model

There are some important differences between the current results and the literature. Unlike previous studies, maximum wind speed never appears in any of the selected models. Furthermore, even when it appears in the Final GUM (see Appendix Table A.2), its effect is never significant. Instead, minimum central pressure is always selected and is statistically significant. This is consistent with Chavas et al. (2017) who show that central pressure is less susceptible than wind speed to measurement errors and also provides a measure of storm power.

Maximum rainfall and storm surge are informative even when wind speed or central pressure are included. An increase in either rainfall or storm surge is associated with a significant increase in damages. This suggests that models which only include wind speed and / or central pressure could under-predict damages. This finding could benefit future forecasts of hurricane damages given that rainfall forecasts already exist and that the National Hurricane Center recently started publishing storm surge warnings.<sup>26</sup>

Natural and climatic forces such as soil moisture and temperature are not selected. This indicates that although they may be informative on their own (see Estrada et al., 2015), they do not provide additional information above and beyond the other variables in the model. However, we cannot say anything about what might determine pressure, rainfall, or storm surges. We cannot rule out that these variables are determined (at least in part) by temperature or other climate variables. The results only suggest that damages from the “natural variability” of hurricanes are not driven exclusively by long-run changes in climate.<sup>27</sup>

The interplay between housing / population and income is an important driver of damages. It suggests that cities are particularly vulnerable to hurricanes since they have both a high building density as well as a high income to housing / population ratio. This is not surprising since the most damaging storms have struck large cities. The results in columns (4) and (5) of Table 6.2 indicate that there is an additional nonlinear affect. Higher income per household has an exacerbating effect on damages. This is in line with Geiger et al. (2016) who find a nonlinear relationship with income. It also indicates that high income areas are particularly vulnerable to damages and that there are possible limits to longer-term adaptation measures.

<sup>26</sup>See NHC (2017), “Update on National Hurricane Center Products and Services for 2017”, [http://www.nhc.noaa.gov/news/20170309\\_pa\\_2017SeasonChanges.pdf](http://www.nhc.noaa.gov/news/20170309_pa_2017SeasonChanges.pdf). Last accessed July 2017.

<sup>27</sup>To explore this further, one could force the climate variables into the model to assess the impact on the coefficients of central pressure, rainfall and storm surge.

The main difference between the current and previous results is the inclusion of forecast errors. The 12-hour-ahead track errors are included across each of the selected models in Table 6.1 and are generally significant for the robust models in Table 6.2. The positive coefficient implies that an increase (decrease) in the forecast error is associated with higher (lower) damages. The results indicate that a 1% increase (decrease) in the forecast error is associated with 0.25 – 0.54% increase (decrease) in hurricane damages respectively. Under strong assumptions<sup>28</sup>, the 67 percent improvement in the 12-hour-ahead forecasts since 1955 is associated with a 17 – 36 percent decline in nominal hurricane damages. Thus, there is a channel through which forecast uncertainty is positively associated with hurricane damages.

## 7 Identifying the forecast impact channel

We already identified three channels through which forecast uncertainty can operate (see section 3). In order to determine whether forecast uncertainty operates through one of the channels, we need to control for the other two. We want to assess if there is evidence of short-term adaptation. Thus, it is necessary to account for the natural variability and long-term adaptation channels. However, data limitations require us to examine the channels individually. First, we focus on the natural variability channel using a sample of hurricanes since 1970. Next, we examine the longer-term adaptation channel using a sample of hurricanes since 1990. Both analyses find that forecast errors remain significant even after accounting for the other channels. This provides support for the operation of the short-term adaptation channel.

### 7.1 Capturing natural variability

The natural variability channel can be controlled for using the forecast errors from a naïve climatology and persistence model. Since naïve forecasts suffer from the same natural variability as the official forecast, partialing out these errors should remove the natural variability channel from the forecast errors. This effectively becomes a measure of forecast “skill”, which is typically used to assess hurricane and weather forecasts; see Cangialosi and Franklin (2016).

Naïve hurricane forecasts are available from the ATCF database for all hurricanes starting in 1970. Forecast “skill” is constructed by taking the ratio of the naïve forecast errors to official forecast errors in logs. An increase in “skill” is associated with either a decline in the official forecast errors or an increase in the naïve forecast errors. The analysis is also extended to longer-horizon forecasts and across different types of damages. Property damages are computed using damage shares from the Storm Events database.<sup>29</sup>

<sup>28</sup>i.e. that improvements in forecast errors were completely exogenous and that the relationship between forecast errors and damages conditional on the other variables in the model is linear and stable over time.

<sup>29</sup>Shares from the storm events database are applied directly to current damages. This assumes that any undercounting of damages in the storm events database is distributed evenly across damage type.

	Total Damages				Property Damages			
	(1) Errors-12	(2) Errors-36	(3) Skill-12	(4) Skill-36	(5) Errors-12	(6) Errors-36	(7) Skill-12	(8) Skill-36
housing density	0.497*** (0.171)	0.543*** (0.180)	0.563*** (0.170)	0.553*** (0.177)	0.526*** (0.177)	0.575*** (0.184)	0.585*** (0.174)	0.579*** (0.181)
income per housing unit	0.985*** (0.316)	0.722** (0.312)	0.879*** (0.305)	0.710** (0.304)	0.960*** (0.328)	0.709** (0.320)	0.903*** (0.311)	0.703** (0.312)
income per housing unit sq.	0.616** (0.240)	0.665** (0.263)	0.611** (0.242)	0.685** (0.268)	0.675*** (0.248)	0.696** (0.269)	0.667*** (0.246)	0.698** (0.275)
min central pressure (-)	52.126*** (9.139)	54.933*** (9.576)	55.663*** (9.184)	55.092*** (9.563)	51.943*** (9.466)	54.093*** (9.810)	55.280*** (9.361)	54.089*** (9.810)
max rainfall	0.640* (0.329)	0.525 (0.343)	0.612* (0.331)	0.502 (0.347)	0.627* (0.341)	0.536 (0.351)	0.616* (0.337)	0.531 (0.356)
max storm surge	1.361*** (0.379)	1.256*** (0.394)	1.293*** (0.380)	1.266*** (0.393)	1.400*** (0.392)	1.313*** (0.404)	1.345*** (0.387)	1.317*** (0.403)
historical fequency	0.570 (2.927)	0.436 (3.094)	-0.220 (2.954)	0.420 (3.072)	1.172 (3.032)	0.929 (3.169)	0.402 (3.011)	0.907 (3.151)
12-hour forecast error	0.580** (0.249)				0.508* (0.258)			
36-hour forecast error		0.095 (0.197)				0.031 (0.201)		
12-hour forecast skill			-0.411** (0.196)				-0.437** (0.199)	
36-hour forecast skill				-0.106 (0.172)				-0.027 (0.176)
$\hat{\sigma}$	1.064	1.112	1.072	1.111	1.102	1.139	1.093	1.139
$R^2$	0.859	0.846	0.857	0.846	0.854	0.844	0.856	0.844
$F_{AR(2)}$	1.896	0.932	1.704	0.953	1.472	1.102	1.723	1.116
$F_{ARCH(1)}$	2.406	0.661	1.975	0.804	1.951	0.368	2.324	0.358
$\chi^2_{nd}(2)$	9.223***	17.937***	10.515***	16.818***	5.257*	11.152***	6.724**	10.946***
$F_{Het}$	1.507	0.746	1.312*	0.849	1.644*	0.723	1.515	0.876
$F_{Het-X}$	1.278	0.949	1.082	0.700	1.204	1.017	1.270	0.754
$F_{RESET23}$	3.643**	3.282**	3.290**	3.475**	3.175**	3.023*	3.084*	3.103*

\*p<0.1 \*\*p<0.05 \*\*\*p<0.01

Notes: All equations are estimated using 65 observations and include a constant and a dummy variable for Floyd [1987]. The standard errors are in parentheses.

**Table 7.1: Controlling for the natural variability channel**

We extend the “baseline” model from section 6 by including the square of income per housing units and the historical frequency of hurricane strikes as a proxy for longer-term adaptation efforts. We focus on how the parameter estimates for forecast errors or forecast “skill” change across horizons and different measures of damages.

Table 7.1 presents the results where columns (1)-(4) look at total damages and columns (5)-(8) are for property damages. In general, there is little distinction between total and property damages. However, the forecast error impact is slightly smaller for property damages.

Longer forecast horizons produce inconclusive results. Although the signs for forecast errors and skill remain consistent across horizons, the longer horizons are not significant. This holds true for the 24- and 48-hour-ahead errors/skill as well (not shown). A possible explanation for this is that the longer-horizon forecast errors are too noisy to identify an impact.<sup>30</sup>

The results indicate that the natural variability channel is not the only channel through which forecast errors operate. Short-horizon forecast “skill” is statistically significant for both total and property damages with a negative sign. This implies that a 1% improvement in forecaster skill is associated with a 0.41% reduction in damages. However, there is also a link between forecast uncertainty and rainfall. This may indicate that forecast uncertainty operates through heavier

<sup>30</sup>One avenue for future research is to use the short-horizon errors as instruments for the long-horizon errors.

than expected rainfalls and flooding. It is supported by the fact that rainfall forecasts rely on hurricane track forecasts (see [Kidder et al., 2005](#)) and that better forecasts can reduce damages from flooding; see [Carsell et al. \(2004\)](#).

## 7.2 Controlling for longer-term adaptation

Longer-term adaptation efforts can be accounted for using various measures. Section 6 implicitly tested for this using historical hurricane frequency, where locations with a higher historical hurricane frequency are more likely to have implemented longer-term adaptation measures. While it was not selected in the final model, it was included (and significant) in the “Final GUM” (see Appendix Table A.2) and could be forced into the “baseline” model.

Longer-term adaptation efforts can also be captured through specific measures. One proxy is the U.S. Federal Emergency Agency’s (FEMA) Community Rating System (CRS) which was established in 1990 as a part of the National Flood Insurance Program to incentivize communities to mitigate flood damages. Communities can voluntarily participate in CRS to take actions to reduce their ratings and pay less for flood insurance. Another proxy is FEMA’s Hazard Mitigation Grant Program (HMGP), which has existed since 1988. This program includes expenditures on a wide variety of damage mitigation efforts, including improving warning systems and removing at risk structures. See [Davlasheridze et al. \(2017\)](#) for more information.

We start with the “baseline” model from section 6 and include the square of income per household and the historical frequency of hurricane strikes. We also include storm-level measures of FEMA’s community ratings (CRS) as well as the cumulative mitigation expenditures (HMGP) as additional controls for longer-term adaptation efforts. Finally, forecast errors from a naïve climate and persistence model are included to control for the natural variability channel.

Table 7.2 presents the results. Comparing the baseline results in column (1) with the other columns provides further support for the short-term adaptation channel. In fact, in column (8), where all of the controls are included, there is little change in the main parameters of interest.<sup>31</sup> Even after controlling for the natural variability and longer-term adaptation channels, forecast errors still have a significant impact on damages. In the absence of any other channels, this supports the operation of a short-term adaptation channel.

## 8 Conclusions

We assess the role that short-term adaptation efforts have played in limiting hurricane damages. In doing so we construct a statistical model of hurricane damages for all hurricanes to strike the continental United States in the past 60 years using a comprehensive set of determi-

<sup>31</sup>Despite being insignificant, CRS has the opposite sign from what was expected. This may indicate that CRS ratings are not exogenous in that communities that are more impacted by extreme weather events are more likely to take measures to mitigate the losses.

	(1) Extended Baseline	(2) CRS	(3) HMGP	(4) CRS +HMGP	(5) Naïve	(6) Naïve +CRS	(7) Naïve +HMGP	(8) Naïve+ CRS+HMGP
housing density	0.644** (0.255)	0.557* (0.278)	0.661** (0.277)	0.564* (0.304)	0.633** (0.262)	0.544* (0.285)	0.650** (0.283)	0.552* (0.311)
income per housing unit	3.973** (1.755)	3.763** (1.783)	3.896** (1.838)	3.734* (1.860)	4.008* (1.785)	3.798** (1.813)	3.927** (1.868)	3.765* (1.892)
income per housing unit sq.	-1.011 (0.934)	-0.897 (0.949)	-1.007 (0.949)	-0.896 (0.965)	-1.045 (0.955)	-0.932 (0.970)	-1.042 (0.970)	-0.932 (0.987)
min central pressure (-)	50.077*** (13.810)	48.418*** (14.020)	50.411*** (14.150)	48.572*** (14.430)	49.570*** (14.120)	47.867*** (14.350)	49.914*** (14.470)	48.039*** (14.760)
max rainfall	0.679 (0.459)	0.702 (0.462)	0.664 (0.474)	0.696 (0.479)	0.692 (0.468)	0.716 (0.471)	0.677 (0.483)	0.709 (0.488)
max storm surge	1.826*** (0.583)	1.944*** (0.603)	1.829*** (0.592)	1.944*** (0.613)	1.829*** (0.591)	1.948*** (0.613)	1.833*** (0.601)	1.949*** (0.623)
historical fequency	0.706 (3.607)	0.105 (3.699)	0.667 (3.670)	0.095 (3.762)	0.930 (3.740)	0.337 (3.830)	0.893 (3.805)	0.328 (3.897)
12-hour official forecast error	0.856** (0.338)	0.935** (0.353)	0.869** (0.351)	0.939** (0.364)	0.848** (0.344)	0.927** (0.359)	0.862** (0.357)	0.932** (0.371)
12-hour naïve forecast error					0.109 (0.376)	0.116 (0.379)	0.112 (0.383)	0.117 (0.385)
Community rating system		-0.266 (0.325)		-0.263 (0.333)		-0.268 (0.330)		-0.265 (0.338)
HMGP spending per capita			0.008 (0.047)	0.003 (0.047)			0.008 (0.047)	0.004 (0.048)
$\hat{\sigma}$	1.184	1.191	1.203	1.210	1.202	1.208	1.221	1.229
$R^2$	0.824	0.828	0.824	0.828	0.824	0.828	0.825	0.828
$F_{AR(2)}$	1.292	1.471	1.266	1.427	1.078	1.267	1.049	1.224
$F_{ARCH(1)}$	2.077	1.390	2.137	1.440	1.513	0.927	1.550	0.968
$\chi^2_{nd}(2)$	2.962	2.699	3.136	2.812	3.313	2.904	3.491	3.033
$F_{Het}$	2.132**	1.970*	1.900*	1.777	2.137**	2.442**	1.970*	2.211**
$F_{RESET23}$	4.247**	3.484**	4.176**	3.511**	4.029**	3.282*	3.941**	3.296*

\*p< 0.1 \*\*p< 0.05 \*\*\*p< 0.01

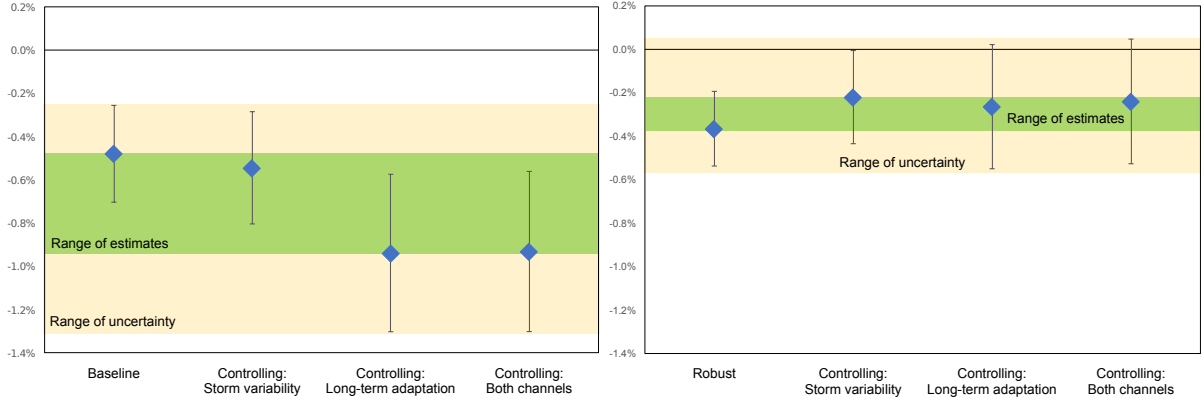
Notes: All equations are estimated using 41 observations and include a constant. The standard errors are in parentheses. The Hetero-X test is excluded due to a lack of observations.

**Table 7.2: Identifying the forecast uncertainty impact channel**

nants previously identified in the literature as well as a handful of new determinants. Simplifying this model in a structured way using a general-to-specific modeling framework which minimizes information loss shows that a small subset of drivers explain much of the variation of hurricane damages. In particular, damages are largely driven by central pressure, rainfall and storm surge as well as through non-linear affects of local income and housing.

We find evidence that short-term forecast uncertainty is associated with hurricane damages. Broadly speaking, the 67 percent improvement in the 12-hour-ahead forecasts over the past 60 years is associated with a 16 – 63 percent decrease in nominal hurricane damages. Figure 8.1 illustrates that this range can be broken into two parts. When outliers are not accounted for then estimated impact is higher and statistically significant despite having a larger variation. Accounting for outliers gives a more reliable range of 16 – 24 percent. However, only the full sample estimate is significantly different from zero.

While forecast uncertainty plays a relatively small role, the improvement in the forecasts has kept damages from rising faster than they otherwise would have. From a policy perspective, even when focusing exclusively on hurricane damages, the results indicate that improvements in hurricane forecasts over the past few decades provided additional benefits beyond the well-documented reduction in fatalities.



Panel A: Baseline

Panel B: Robust

Note: Panel A compiles the estimates for the 12-hour-ahead forecast errors from the baseline model in Tables 6.2, 7.1 and 7.2 including the squared term and historical frequency. Panel B presents the same results while also including dummies for the outliers from Table 6.2 in all cases. The sample sizes vary from 98 – 41 observations.

**Figure 8.1: Estimated effect of a 1% improvement in hurricane track forecasts on damages**

The evidence also supports the interpretation that the link between forecast uncertainty and damages is interpretable through the short-term adaptation channel. We find a significant relationship even after controlling for other channels. Overall, this suggests that short-term efforts can result in significant (albeit relatively small) reductions in damages from extreme weather and climate events. Thus, when facing an increasingly volatile climate, there is value in enacting policies that encourage adaptation to change across all horizons.



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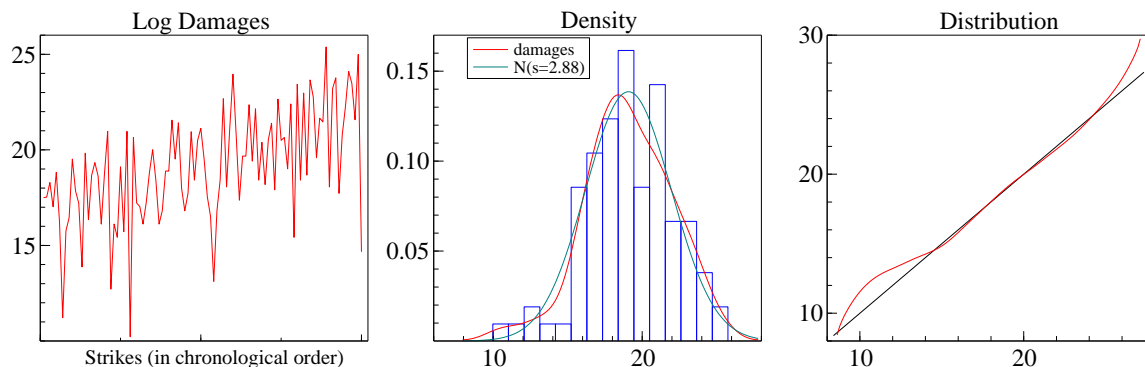
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# Appendix

## A Additional Figures and Tables



Note: Hurricane damages are the logs of the nominal values of hurricane damages for each hurricane strike.

**Figure A.1: Hurricane Damages**

Variable	Description	Years	Min	Average	Max	Source
<b>Impacts</b>						
DAMAGE	Nominal Damage (U.S. \$1,000 )	1955-2016	\$28	\$3,990,506	\$105,900,000	NOAA, NHC
PDAMAGE	Nominal Property Damage (U.S. \$1,000 )	1970-2015	\$500	\$5,125,996	\$100,699,947	NOAA, NHC / NCEI
<b>Natural Determinants</b>						
WIND	Max Sustained Wind Speed (kt)	1955-2016	65	90.3	150	NOAA, HRD
PRESS	Central Pressure at Landfall (mb)	1955-2016	909	965	1003	NOAA, HRD
RAIN	Max Rainfall (in)	1955-2016	4.8	13.75	38.5	NOAA, WPC
SURGE	Max Surge (ft)	1955-2016	0	8.5	27.8	NOAA, NHC
ACE	Accumulated Cyclone Energy (Season)	1955-2016	17	135	250	NOAA, HRD
CAT	Max Hurricane Category (Saffir-Simpson)	1955-2016	1	2	5	NOAA, HRD
MOIST	Deviations from trend soil moisture (in)	1955-2016	-4.75	1	5.7	NOAA, ESRL
GST	Land, Air and Sea-Surface Temp. index	1955-2016	0.1	0.34	0.93	NASA, GISS
<b>Socio-Economic Determinants</b>						
PD	Population Density (persons per acre)	1955-2015	12	257	3,940	BEA, Census
ID	Income Density (\$1,000 per acre)	1955-2015	\$11	\$6,714	\$237,255	BEA, Census
IP	Income Per Capita (\$ per person)	1955-2015	\$864	\$16,430	\$60,213	BEA
HD	Housing Units (houses per acre)	1955-2015	5	104	1,672	Census
IH	Income Per Housing Unit (\$1,000 per unit)	1955-2015	\$2	\$37	\$140	BEA, Census
FREQ	Historical Hurricane Frequency (Average per year)	1955-2016	0.01	0.09	0.32	NOAA, HRD
CRS	FEMA Community Rating System (rank)	1990-2016	7	9	10	FEMA
HMGP	Hazard Mitigation Grant Program (U.S. \$1,000)	1990-2016	0	\$38,042	\$396,102	FEMA
<b>Behavioral Determinants</b>						
MAFEM	Masculinity/Femininity Name Index	1955-2014	1.06	6.79	10.44	<a href="#">Jung et al. (2014)</a>
WARN	Hurricane Warning Lead Time	1955-2016	1	25	66	NOAA, NHC
<b>Forecasts</b>						
FORC12	12-Hour Official Track Error (nautical miles)	1955-2016	5	34	114	NOAA, NHC
CON12	Implied 12-hour cone of uncertainty (nautical miles)	1955-2016	34	70	59	NOAA, NHC
NAIVE12	12-Hour Naïve Track Error (nautical miles)	1970-2016	5	31	97	NOAA, NHC
SKILL12	Ratio of 12-Hour naïve forecast error to FORC12	1970-2016	0.19	1.44	10.35	NOAA, NHC

**Table A.1: Descriptions and Summary Statistics**

Selection Target:	1%		2%		3%		4%		5%	
Model:	FGUM	Pooled (13)	FGUM	Pooled (12)	FGUM	Pooled (12)	FGUM	Pooled (14)	FGUM	Pooled (12)
population density	-8.5×10 <sup>4</sup>	-3.9×10 <sup>3</sup>	1.277	0.438	-7.5×10 <sup>4</sup>	-6.9×10 <sup>3</sup>	1.289	0.615	1.076	0.338
housing density	8.5×10 <sup>4</sup>	3.9×10 <sup>3</sup>	-0.754	0.067	7.5×10 <sup>4</sup>	6.9×10 <sup>3</sup>	-0.781	-0.027	-0.509	-0.272
income per household	8.5×10 <sup>4</sup>	3.9×10 <sup>3</sup>	0.932	0.772	7.5×10 <sup>4</sup>	6.9×10 <sup>3</sup>	0.990	0.480	0.900	0.579
income per capita	-8.5×10 <sup>4</sup>	-3.9×10 <sup>3</sup>	.	.	-7.5×10 <sup>4</sup>	-6.9×10 <sup>3</sup>	.	.	.	.
historical fequency	-6.015**	-3.647	-6.167**	-3.298	-6.401**	-4.040	-6.182**	-5.706	-6.370**	-4.051
max rainfall	0.605*	0.305	0.614*	0.654	0.590*	0.671	0.620	0.207	0.607	0.539
max storm surge	1.131**	1.199	1.374***	1.219	1.159**	1.293	1.306**	1.149	1.416**	1.198
min central pressure (-)	68.158***	64.481	64.949***	59.750	68.981***	56.970	67.454***	65.670	70.150***	65.886
max wind speed	0.074	-0.032	-0.097	-0.211	.	.	-0.186	-0.107	-0.025	-0.154
max hurricane category	-0.460	-0.237	-0.376	-0.093	-0.406	-0.115	-0.390	-0.196	-0.453	-0.218
seasonal cyclone energy	0.186	0.152	0.219	0.058	0.211	0.137	0.175	0.109	0.225	0.115
soil moisture	.	.	.	.	.	.	.	.	0.143	0.031
12-hour forecast error	0.654**	0.183	0.546**	0.333	0.638**	0.362	0.596**	0.150	0.514**	0.243
year trend	.	.	-0.022	-0.023	.	.	-0.015	-0.025	-0.019	-0.028
strike trend	0.014	0.008	.	.	.	.	0.004	0.009	.	.
00:00 UTC	.	.	.	.	472.63***	30.138	-0.322	71.226	.	.
06:00 UTC	.	.	.	.	472.62***	30.091	-0.381	71.216	.	.
12:00 UTC	.	.	0.350	0.090	473.00***	30.253	0.000	71.537	0.442	0.116
18:00 UTC	.	.	0.462	0.054	473.07***	30.155	0.102	71.346	0.489	0.064
JUN	-1.145*	-0.241	-0.545	-0.388	-1.242**	-0.573	-0.545	-0.131	-0.959	-0.192
JUL	-0.775	-0.162	.	.	-0.583	-0.110	.	.	.	.
AUG	.	.	0.584	0.064	.	.	0.658	0.047	.	.
SEP	-0.183	0.032	0.482	0.055	.	.	0.498	0.102	0.015	0.038
OCT	.	.	0.493	0.065	.	.	0.496	0.035	.	.
MA	1.949	0.545	1.756	0.028	.	.	.	.	1.963	0.028
RI	.	.	-1.115	-0.323	.	.	.	.	-1.234	-0.283
CT	-0.444	-0.321	0.000	-0.011	.	.	0.068	-0.339	0.000	-0.144
NY	-1.913	-0.867	-1.584	-0.398	-1.606*	-0.484	-1.655	-0.613	-1.631	-0.538
MD	.	.	0.715	0.233	.	.	.	.	.	.
VA	.	.	.	.	.	.	1.175	0.322	.	.
NC	0.002	-0.076	.	.	-0.311	-0.037	-0.007	-0.132	-0.033	-0.135
FL	0.682*	0.185	0.796**	0.285	0.674*	0.437	0.818**	0.451	0.776*	0.240
AL	0.432	0.038	.	.	.	.	.	.	.	.
$\hat{\sigma}$	1.195	1.152	1.215	1.145	1.176	1.122	1.236	1.147	1.222	1.151
$R^2$	0.868	0.840	0.867	0.842	0.870	0.849	0.865	0.842	0.864	0.840
$F_{AR(2)}$	0.780	0.333	0.499	0.203	1.617	0.352	0.754	0.246	0.465	0.183
$F_{ARCH(1)}$	3.809*	2.224	1.342	1.605	2.590	1.189	0.839	0.955	2.241	1.339
$\chi^2_{nd(2)}$	2.059	9.773***	4.576	9.284***	0.874	6.173***	3.832	9.374***	5.126*	9.558***
$F_{Het}$	1.714**	2.473***	1.134	1.656**	1.539*	2.550***	1.095	1.665**	1.135	1.569*
$F_{RESET23}$	0.399	.	0.542	.	0.304	.	0.509	.	0.229	.

\*p< 0.1 \*\*p< 0.05 \*\*\*p< 0.01

Notes: All equations are estimated using 98 observations and include a constant and dummy variables for Gerda [1969] and Floyd [1987]. Selection target refers to the target value (target size) at which model selection occurs. FGUM is the final selected GUM at a given selection target. Pooled is the average of the coefficient values of the terminal models at a given selection target, where the number of terminal models is in parentheses.

**Table A.2: Estimated Coefficients from Final GUM and Pooled Terminals**

	pd	hd	ih	ip	Freq	rain	surge	press	wind	Moist	Cat	ace	GST	forc12	con12	Name	Trend
dam	<b>0.51</b>	<b>0.51</b>	<b>0.59</b>	<b>0.54</b>	-0.14	0.32	<b>0.54</b>	<b>0.60</b>	0.34	0.09	0.40	0.30	<b>0.52</b>	-0.25	-0.43	-0.14	<b>0.53</b>
pd		<b>0.98</b>	<b>0.55</b>	0.49	-0.02	0.14	0.12	0.11	-0.01	-0.02	0.02	0.05	0.39	-0.15	-0.29	-0.07	0.41
hd			<b>0.64</b>	<b>0.61</b>	0.01	0.11	0.08	0.09	-0.05	-0.01	-0.02	0.08	0.50	-0.19	-0.36	-0.11	<b>0.53</b>
ih				<b>0.99</b>	0.02	0.11	0.07	0.05	-0.15	0.00	-0.12	0.21	<b>0.93</b>	-0.42	<b>-0.63</b>	-0.38	<b>0.95</b>
ip					0.04	0.07	0.03	0.02	-0.18	0.01	-0.14	0.21	<b>0.94</b>	-0.42	<b>-0.64</b>	-0.38	<b>0.97</b>
Freq						-0.17	-0.10	-0.04	0.12	0.05	0.08	0.03	0.01	-0.04	-0.03	-0.16	0.02
rain							0.09	0.11	0.01	0.22	0.05	0.19	0.14	-0.24	-0.20	-0.14	0.12
surge								<b>0.65</b>	<b>0.52</b>	0.11	<b>0.60</b>	0.08	0.01	-0.10	-0.09	0.06	0.01
press									<b>0.81</b>	-0.02	<b>0.85</b>	0.18	0.03	-0.01	-0.14	0.08	0.01
wind										0.03	<b>0.88</b>	0.12	-0.20	0.08	0.08	0.10	-0.19
Moist												0.04	0.08	0.01	-0.02	-0.01	-0.02
Cat													0.06	-0.16	0.05	0.06	-0.17
ace														0.35	-0.26	-0.43	-0.01
GST															-0.46	<b>-0.79</b>	-0.36
forc12																0.43	0.10
con12																	0.16
Name																	-0.36

**Table A.3: Bivariate Correlations**



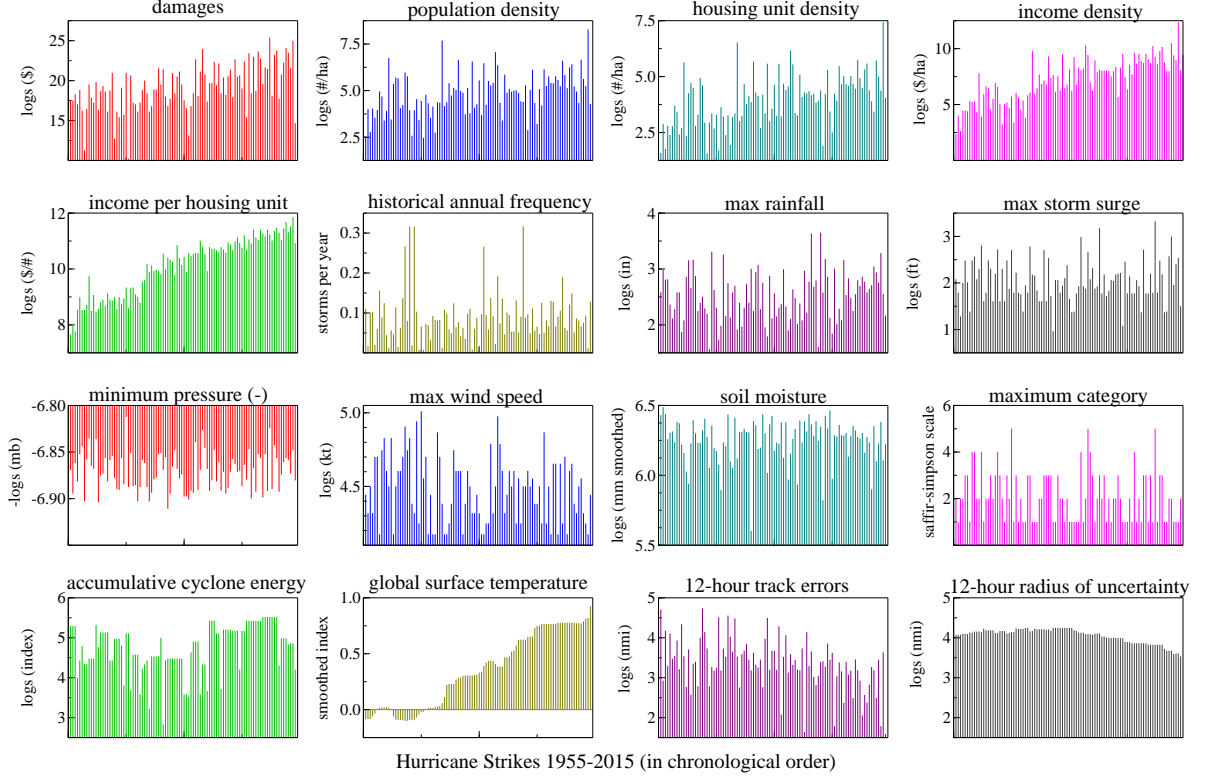


Figure A.2: Data Plots

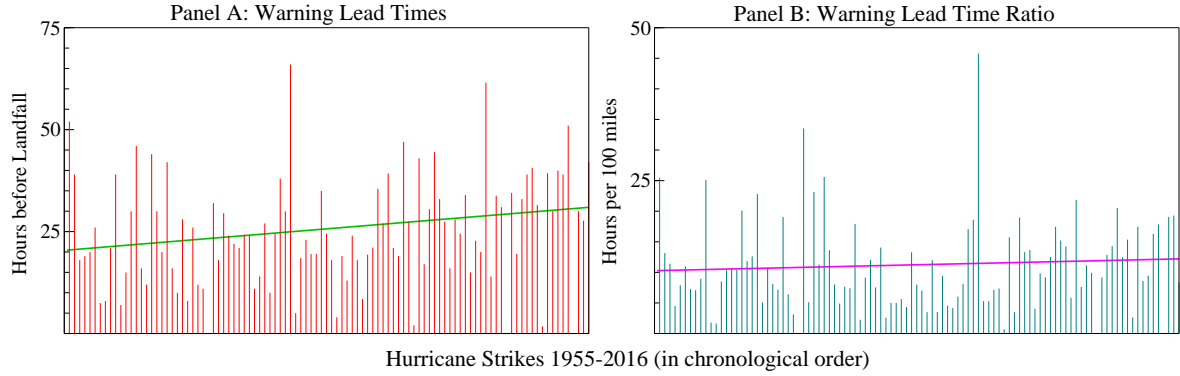
## B Additional Data Descriptions

### B.1 Hurricane Warnings

Storm warnings and watches are the most prominent outputs for hurricane forecasts. There are four watch / warning types. The lowest level is a tropical storm (formerly gale) watch, indicating that tropical storm force winds are expected in that area in the next 48 hours (historically 36). The next level is a tropical storm warning which indicates that tropical storm force winds are expected within the next 36 hours (historically 24). Next are Hurricane watches and warnings respectively which indicate that Hurricane force winds are expected within the same time horizons.

Hurricane warnings are a crucial part of the U.S. government's evacuation system. They are coordinated with local authorities and used as a precursor for whether an evacuation order is given. For this reason, hurricane warnings do not always follow the rule that the hurricane force winds will be experienced within the next 24-36 hours but rather take into account how much time a given area would need to be evacuated. Given this close association, hurricane warnings serve as a proxy for hurricane evacuations (although they do not translate directly into evacuation orders).

One might expect that earlier hurricane warnings allow for more preparation and are there-



Note: Hurricane warning lead times are computed as the number of hours prior to making landfall the first warning was issued for the actual landfall location. The warning lead time ratio is computed as the warning lead time divided by the (straight line) distance in miles which the initial warning covered to proxy the uncertainty surrounding the warning area.

**Figure B.1: Hurricane Warnings**

fore associated with lower damages, whereas later warnings are associated with higher damages. However, given that warnings are tied with evacuations and often determined based on the expected strength of the storm and the lead time required in evacuating large numbers of people, this complicates the expected relationship. In particular, earlier warnings may be given for stronger storms or when they are expected to strike more populated locations. Thus, the expected relationship with damages is unclear.

The uncertainty associated with a warning also complicates its effectiveness. While there are incentives to providing earlier warnings (as Panel A of Figure B.1 shows), there is an inherent trade-off between providing earlier warning times and more focused warning areas. Earlier warning times implies that given the uncertainty associated with the path of the hurricane there is a greater possibility that the warning covers a larger area. As Panel B of Figure B.1 shows, despite the fact that the hurricane warning lead times have increased over the sample, the ratio of the hurricane warning lead time to the area covered under that initial warning has been fairly stable across most hurricanes which illustrates that there is a relationship between the increase in warning lead-time and the area being warned.<sup>32</sup>

## B.2 Impact Areas

A crucial aspect for any model of hurricane damages is the determination of which geographical locations are actually impacted. Although damages are generally only available at the storm or strike level, most other data used to capture determinants of damages are given at the U.S. county level. Thus, it is important to establish which counties were impacted.

A simple approach is to use direct coastal hurricane strikes. This approach is widely used in the literature, see Jarrell et al. (1992), but suffers from several drawbacks. In particular, it may under count hurricane damages by excluding inland counties that experienced a direct

<sup>32</sup>This is a very crude measure since some hurricanes do in fact affect a wider area (e.g. a Hurricane that travels along the entire east coast of the United States) and so a wider warning area is actually a good thing.

strike. It also excludes other coastal communities that were indirectly affected by the hurricane through rain, wind or storm surges. Thus, while the approach is used here for simplicity, it likely underestimates the impact of some variables and overestimates the impact of others.

Given the shortcomings of the direct coastal strike approach, there are various methods used in the literature to determine the impact area. A popular approach used by [Strobl \(2011\)](#), [Deryugina \(2017\)](#) and others is to simulate wind speeds in surrounding counties using the actual hurricane track and intensity data. While this is a useful approach it also has its own shortcomings. First, it requires a cutoff value for either the wind speeds or the surrounding area. [Bakkensen and Larson \(2014\)](#) choose the five counties around the initial landfall as the cutoff. On the other hand, [Strobl \(2011\)](#) and [Deryugina \(2017\)](#) include all counties that fall within the maximum wind speed radius of the storm. By focusing exclusively on wind speeds, this approach implicitly gives a higher weight to wind damages and may miss other important important drivers of damages.

Another approach is to focus on counties which are declared disaster areas.<sup>33</sup> This approach also has several drawbacks. First, not all hurricanes have counties that are declared disaster areas so it under-counts the impact of smaller hurricanes. Second, disaster declarations are a political decision that can result in significant differences over time and across U.S. states. Finally, in some cases disaster declarations for larger storms are made in advance of the actual storm and so may over count the actual impact of the hurricane. Figure [B.2](#) illustrates the differences between direct hurricane county strikes versus disaster declarations.

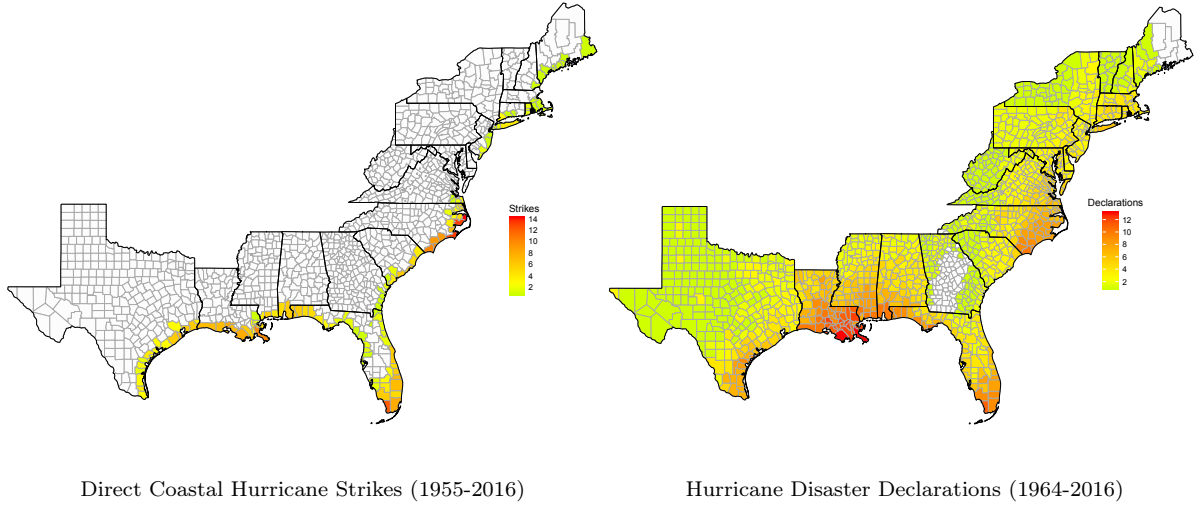
A better approach would be to determine areas based on actual damages. However, damages are typically only available for the storm rather than at the state or county level. Furthermore, sources that do collect storm damages at the county level (i.e. the Storm Events database), tend to severely underestimate damages. One way around this is to assume that any under-reporting is random so that the approximate impact shares per county are unaffected. This may give more precise measurements of the impact area and would also allow for the analysis to be done at the county rather than the storm or strike level.<sup>34</sup>

### B.3 Soil Moisture

Model-based estimates of monthly average soil moisture from 1948-2017 using methods devised by [van den Dool et al. \(2003\)](#) were collected from NOAA's Earth System Research Laboratory. The data was linked to counties through the nearest grid point to a given county's

<sup>33</sup>See the U.S. Federal Emergency Management Agency's website on disaster declarations for a list of disaster counties from each hurricane.

<sup>34</sup>Note that some studies, notably [Strobl \(2011\)](#), have conducted their analysis at the census tract level. However, they first determine a relationship between wind speed and damages at the storm level and use these estimates to conduct their analysis at a more dis-aggregated level.



Note: Direct Coastal Hurricane Strikes uses and updates the data from the county by county hurricane strikes maintained by NHC HRD for all landfalling hurricanes from 1955-2016. Hurricane Disaster Declarations are taken from FEMA's Disaster declaration database and only includes declared disasters for landfalling hurricanes from 1964-2016.

**Figure B.2: Hurricane Impact Areas**

centroid. The individual county estimates were then averaged across counties that were struck by a given hurricane and then estimates were smoothed using an HP filter where the smoothing parameter is set to 129,600 following the results of [Ravn and Uhlig \(2002\)](#) for monthly data. The smoothed series is then paired with the particular month that the hurricane struck. The choice of contemporaneous or lagged month does not affect the results.

#### B.4 Historical Frequency

The historical frequency of hurricane strikes is computed by taking historical hurricane strikes at the county level since 1900. The expected number of hurricanes in a given year and county is computed over time by taking the number of hurricane strikes that have occurred in a county since 1900 and then dividing that by the number of years that have passed since 1900. The historical frequencies for a given storm are then computed by taking a simple average of the historical frequencies for all counties that were struck by the storm. An alternative measure of historical frequency is computed by calculating the number of months since the last hurricane strike in a given county over time. This is then averaged across all countries that were struck by a hurricane to get a storm level frequency.

#### B.5 Temperature

Sea surface air temperature is computed following [Estrada et al. \(2015\)](#). The data was collected from NASA's global mean surface temperature index based on land-surface air temperature anomalies. The monthly series is then smoothed using an HP filter where the smoothing parameter is set to 129,600 following the results of [Ravn and Uhlig \(2002\)](#) for monthly data. The choice of this parameter does not have a large impact on the results. The smoothed series is then

paired with the particular month that the hurricane struck. The choice of contemporaneous or lagged month does not affect the results.

## B.6 Rainfall

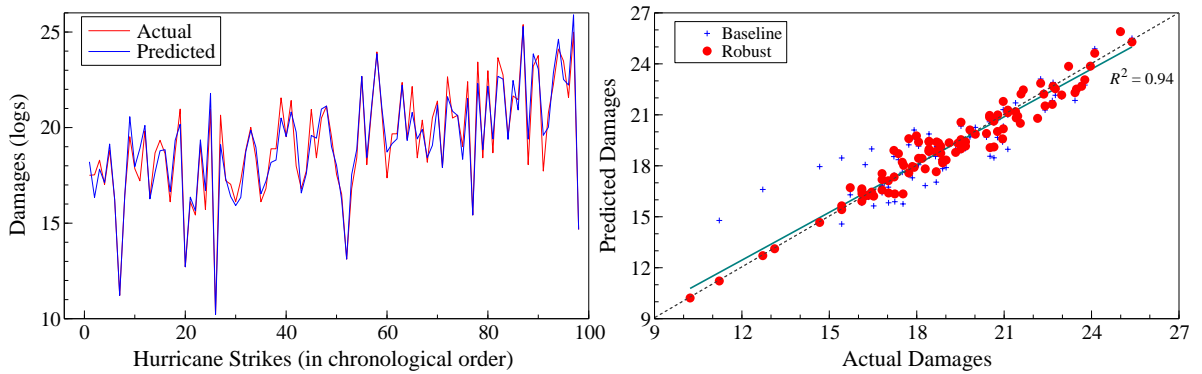
Maximum rainfall is available from NOAA’s weather prediction center for all tropical cyclones. The values chosen are the highest rainfall values for a given hurricane in inches. When a given hurricane struck multiple areas, the highest amount of rainfall was chosen based on the location surrounding that landfall.

## B.7 Storm Surge

Storm surge was collected from historical tropical cyclone and seasonal reports. Storm surge is generally based on the highest estimated surge for a given storm. While every attempt was made to standardize measures across storms, varying definitions are used. These include number of feet above the mean sea level or above high tide. Wherever possible mean sea level was used. However in some cases it was not available. Furthermore, some observations rely on estimates from a storm surge model due to the perceived unreliability of observations.

## C Assessing Model Fit

One way to assess a model is by looking at the goodness of fit. The  $R^2$  suggests that the baseline model in column (1) of Table 6.2 captures about 82 percent of the variation in damages, whereas the robust model in column (4) captures about 94 percent of the variation. Figure C.1 presents two alternative approaches for assessing the fit of the model. The left-hand panel presents the actual and the predicted damages from the robust model. The right-hand panel compares the predicted vs. actual damages for both the baseline and robust models. It illustrates that the baseline model tends to over-predict the impact of the least damaging hurricanes. Given that several of these hurricanes are earlier in the period, it could also suggest that in some cases the damages were under-reported.



Note: Hurricane damages are the logs of the raw nominal values of hurricane damages for each hurricane strike.

**Figure C.1: Model Fit**

Another way to assess the model is to see how well it does in an in-sample model comparison exercise. One way to do this is to perform a model encompassing test; see [Chong and Hendry \(1986\)](#) and [Mizon and Richard \(1986\)](#). A common variant of this approach is to estimate a simple regression model where hurricane damages are explained using fitted values from each model. Encompassing tests are performed by testing restrictions on the parameters.

For this exercise the “baseline” model and the “robust” model from columns (1) and (4) of Table 6.2 respectively are considered. Two additional models are included for comparison. The first is a quasi-replication of the model proposed by [Bakkensen and Mendelsohn \(2016\)](#) (hereafter “BMP”), which includes income per capita, population density, minimum central pressure, historical hurricane frequency and state level controls.<sup>35</sup> The second is a replication of the approach used in [Nordhaus \(2010\)](#) and [Strobl \(2011\)](#) (hereafter “NSW”) where the coefficient on income is set to 1 while estimating the relationship with maximum wind speed.

The estimation results for the sample from 1955-2015 are as follows:

$$\begin{aligned} \text{damage}_i = & -0.38 - 0.17 \times \widehat{\text{Baseline}}_i + 0.97 \times \widehat{\text{Robust}}_i + 0.17 \times \widehat{\text{BMP}}_i + 0.02 \times \widehat{\text{NSW}}_i \quad (\text{C.1}) \\ & (0.58) \quad (0.10) \quad (0.08) \quad (0.09) \quad (0.05) \end{aligned}$$

$$N = 98 \quad \hat{\sigma} = 0.707 \quad R^2 = 0.941.$$

where the standard errors are in parentheses. Does the “robust” model explain the results of other models? We can answer this by testing the joint null hypothesis that the coefficient for “robust” in equation (C.1) is equal to 1 while all other model coefficients are equal to 0. When these restrictions are imposed, a Wald-type test statistic of 0.274 is obtained. Comparing this value against an F-distribution with (2, 93) degrees of freedom indicates that the null hypothesis is not rejected at any standard level of significance. It is also supported by the fact that the  $\hat{\sigma}$  and  $R^2$  values in equation (C.1) are practically unchanged when compared against the same values in column (4) of Table 6.2. In other words, the information contained within the “robust” model sufficiently explains all of the changes captured by other models. This is not surprising since model encompassing forms the backbone of the GETS approach.

It is also useful to compare model performance in an out-of-sample forecasting exercise. Extending the sample through 2016 gives two additional hurricanes that can be used in this exercise: Hermine [2016] and Matthew [2016]. They provide a useful test of the models since Hermine caused relatively little damage (\$550 million) while Matthew was highly destructive (\$10 billion). The models are estimated over the sample 1955 – 2015. The parameter estimates are used, ignoring any uncertainty, to “predict” damage from the 2016 hurricanes based.

<sup>35</sup>Note that this is not an exact replica since the original model uses a long-run simulated frequency of high and low intensity storms. There is also another version of the model which uses maximum wind speed instead of central pressure, however pressure does best here.

	Hermine				Matthew				Average		
	Forc.	Error	AE	PE	Forc.	Error	AE	PE	Error	AE	PE
"Baseline"	0.63	<b>-0.08</b>	<b>0.08</b>	<b>-14.89</b>	1.65	8.35	8.35	83.54	4.14	4.22	34.33
"Robust"	0.86	-0.31	0.31	-56.81	2.75	7.25	7.25	72.48	3.47	3.78	<b>7.83</b>
"BMP"	1.26	-0.71	0.71	-128.39	1.61	8.39	8.39	83.91	3.84	4.55	-22.24
"NSW"	1.55	-1.00	1.00	-181.18	7.06	<b>2.94</b>	<b>2.94</b>	<b>29.38</b>	<b>0.97</b>	<b>1.97</b>	-75.90

Notes: Forecasts (Forc.), errors (Error), and absolute errors (AE) are in billions of U.S. dollars. Errors are calculated as the actual damages minus the predicted damages so that a positive error is indicative of under-prediction. Percentage errors (PE) are in percent of actual damages. Actual damages are taken from the respective Tropical Cyclone Report available from NOAA. Bold terms indicate the model that does best for each metric.

**Table C.1: Evaluating “forecasts” of damages from the 2016 hurricane season**

Table C.1 presents the forecasts and their errors for both storms across the different models. The results illustrate that the “robust” model forecast is neither the worst nor the best forecast. The “baseline” model performs best for Hermine followed closely by the “robust” model. The “NSW” model does best for Matthew (despite a massive over-prediction for Hermine) followed in a distant second by the “robust” model. The “robust” model is therefore less susceptible to whether the hurricane is a low or high damaging storm. “NSW” maintains its dominance when averaging between the two hurricanes due to massive forecast failure for Matthew [2016].<sup>36</sup> This indicates that the aggregate models do not perform very well for storms, such as Matthew [2016], whose damages were spread across a wide geographic area. It also suggests that the length of coastline affected could be a useful addition to the model.

<sup>36</sup>Some of this failure may be due to the fact that the reported damage value from the Tropical Cyclone report for Hurricane Matthew was taken from the Billion Dollar events database. Given that the damage estimates used are on average about 4% lower than those of the Billion Dollar events database then this may account for some of the error. However, it does not count for all the error since the reported damages from the Storm Events database for Hurricane Matthew are approximately \$4 billion. Note also that the “NSW” model does even better when central pressure is included instead of wind speed.