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The fertility effect of catastrophe: U.S. hurricane births

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Abstract Anecdotal evidence has suggested increased fertility rates resulting from catastrophic events in an area. In this paper, we measure this fertility effect using storm advisory data and fertility data for the Atlantic and Gulf-coast counties of the USA. We find that low-severity storm advisories are associated with a positive and significant fertility effect and that high-severity advisories have a significant negative fertility effect. As the type of advisory goes from least severe to most severe, the fertility effect of the specific advisory type decreases monotonically from positive to negative. We also find some other interesting demographic effects.

Keywords Fertility · Family planning · Models with panel data · Disaster

JEL Classification J13 · C23

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1 Introduction

As with the New York City blackout of 1965, the Oklahoma City bombing of 1995, and the terrorist attacks of September 11, 2001, the press have reported increased birth rates 9 months after tropical storms and hurricanes. Pedicini (June 7, 2005) reported in the *Orlando Sentinel* what was reported by multiple other news agencies—that the storms that hit Florida during the 2004 hurricane season had generated a baby boom. However, until recently, the results of studies trying to measure similar effects have been mixed.[1] Our aim in this study is to quantify the fertility effect of catastrophes using US storm advisory data from 1995 to 2001 and US birth data from 1996 to 2002.[2]

The fertility effect of catastrophe is important to economists, demographers, and policy makers in general because it illuminates how individual fertility decisions are influenced by changes in expectations about the costs and benefits of child rearing in the future. This question is also of great importance, in particular, to policy makers in areas that experience storm warnings on a regular frequency. Our study brings together in one a number of results that have been found separately in the literature (see Section 2). Examples include low-severity events, such as the great New York City blackout of 1965, increasing fertility rates 9 months later. Others have shown that high severity events – such as famines, war, and terrorism – can have either a positive or a negative fertility effect. Our analyses are uniquely tailored to measure the fertility effect of catastrophe because our data include a series of events of varying catastrophic intensity.

In our study, we chose to try to measure the fertility effect of catastrophe using storm advisory data.[3] US storm advisory data represent a time series of multiple-severity exogenous shocks that influence a large number of Atlantic and Gulf Coast counties for which we have detailed birth data. Using our rich storm advisory data in combination with US county birth data, we are able to estimate the fertility effect of these weather catastrophes.

The uniqueness of this study is its use of exogenous storm advisory shocks over a significant time period, its large sample area of US counties, and the variation in severity of the shocks. Until recently, previous attempts to measure the fertility effect of a catastrophe have carried out only single-shock experiments observed in a single area (usually one county or city), so that

[1] Udry (1970) finds no effect from the 1965 New York City blackout but Rodgers et al. (2005) find a positive effect after the Oklahoma City bombing.

[2] Studying different effects of hurricane impacts has attracted some attention in economics recently. Belasen and Polachek (2008) study the impact of hurricanes on local labor markets in Florida. Pörtner (2008) examines the interaction among hurricane risk, fertility, and education outcomes in developing countries. Yang (2006) investigates the impact of hurricanes on international capital flows.

[3] We discuss in detail the reasons why we chose to use storm advisories instead of actual storm paths in Section 4.1. Appendix A2 provides a detailed comparison of the benefits and drawbacks of using storm advisory data over actual storm path data.

they observe no variations in catastrophe severity or frequency. The data we use here not only allow us to study the impact of catastrophe on fertility but also enable us to characterize the relationship between fertility levels and catastrophe severity.

Our main findings are that low-severity storm advisories are associated with a positive and significant fertility effect and that high-severity advisories have a significant negative fertility effect. As the type of advisory goes from least severe to most severe, the fertility effect of the specific advisory type decreases monotonically from positive to negative. We also find that most of the changes in fertility resulting from storm advisories come from couples who have had at least one child already. In addition to our short-term effect estimation, we also test the effects of storm advisories on long-run fertility. Our results provide weak evidence that the highest-severity storm advisories have a permanent negative fertility effect.

The paper is organized as follows: Section 2 briefly reviews the relevant literature, Section 3 discusses related theories and channels through which storm advisories could affect fertility, Section 4 describes the data used in the paper, Section 5 presents the empirical results, Section 6 is a robustness check, and Section 7 concludes.

2 Literature

The seminal empirical paper in this literature is that by Udry (1970). He studied the great New York City blackout of November 9, 1965, in which the city lost electrical power for as long as 10 h in some areas. Nine months after the power outage, Tolchin (August 10, 1966) reported in *The New York Times* that several local hospitals had experienced record-high single-day births—in some cases, more than doubling the number of births on that day in the previous year.

Using daily birth total data from the New York City Health Department for the years 1961 to 1966 and using available gestation period data, Udry (1970) assumed that 90% of the babies conceived on the date of the blackout would be born within a roughly 3-week range centered 266 days (38 weeks) from the date of the blackout. Calculating the mean births for each day in the same 3-week period in the previous 5 years, Udry found that the increase in New York City births 9 months after the blackout was not more than two standard deviations greater than the mean daily value of previous years on any given day. Using this simplistic procedure with no controls and a very small sample size, he concluded that there was no positive fertility effect resulting from the blackout.

A more recent study by Rodgers et al. (2005) is a step forward because they look at more extensive time series data for a number of counties controlling for county- and time-specific characteristics. They estimate the effect of the Oklahoma City bombing on fertility rates in the surrounding counties. They find a positive fertility effect for the area immediately surrounding Oklahoma

City 9 months after the bombing.[4] The primary weakness of the studies by Udry (1970) and Rodgers et al. (2005) is that they only have one shock and, therefore, have no variance in the frequency or severity of the shock.

Lindstrom and Berhanu (1999) study the impact of war and famine on marital fertility in Ethiopia. They find strong evidence of short-term fertility decrease after famine, war, or economic upheaval. The events examined in their paper are more likely to be permanent or long-term shocks compared with the storm advisories studied here. For example, Belasen and Polachek (2008) find that the effect of hurricane shocks on growth rates of earnings are temporary, and the effects last roughly 2 years. It is interesting that they find a hurricane-stricken region experiences positive earnings growth, while its nearby unaffected regions experience negative growth. They rationalize this finding on the grounds that a hurricane-stricken region will have a negative labor supply shock after the hurricane since people will flee to unaffected regions, and this outflow of people will create a positive labor supply shock for the nearby unaffected regions.

Among the studies by economists, that by Pörtner (2008) is the closest to our work. He studies how educational level and fertility behavior respond to hurricane risk and shocks in Guatemala over the last 120 years. His main focus is on using education and fertility decisions as insurance strategies when households face risk. He concludes that, while hurricane risk leads to an increase in fertility, actual hurricane shocks result in decreasing fertility. However, his sample is restricted to developing countries and focuses more on long-term fertility effects.

3 Theory and channels

Regarding theoretical explanations for a fertility effect of storm advisories, economics has many models to explain fertility behavior. The static models include the quality–quantity model of Becker (1960) and the time allocation model of Mincer (1963). The life-cycle models, such as those by Hotz and Miller (1985), Moffitt (1984a), and Rosenzweig and Schultz (1985), characterize the optimal number of births and their optimal timing. Becker and Barro (1988) go a step further and formulate a dynastic model that explains fertility rates and capital accumulation across generations.[5]

[4]The idea of the fertility rate increasing during periods in which individuals' expectations about the future become less certain has been addressed in the demographic, economics, and sociological literature. Examples include Cain (1981, 1983), and Pörtner (2001), among others. Robinson (1986) refers to this phenomenon as the "risk insurance hypothesis," and it is commonly used to explain why poorer countries have higher birth rates.

[5]See Hotz et al. (1997) and Schultz (1997) for extensive reviews of theoretical fertility models, as well as empirical studies on developed and developing countries.

Several channels exist through which storm advisories could affect fertility.[6] The first channel is how individuals allocate time immediately after the weather service issues an advisory. One might expect individuals to behave differently according to the severity of an advisory. During a low-level advisory, people might spend more time at home, leading to more sexual activity because the opportunity cost of leisure is lower. During a high-level advisory, the opportunity cost of leisure increases, and individuals are more likely to be occupied by other precautionary activities, such as shopping for necessities and covering the windows with plywood. This will lead to less sexual activity.

Indeed, the National Oceanic and Atmospheric Administration (2007, NOAA) has prepared a document that informs coastal residents what to do in the case of each level of storm advisory. Regarding the lower-severity storm *watches*, the NOAA advises coastal residents to frequently listen to the television and radio for warnings and to stock up on supplies. Except in the case of individuals who live in mobile homes or on islands, the listed precautions for watches mainly deal with what to have ready in order to ride out a storm at a coastal residence. However, the instructions for the more severe storm *warnings* mainly deal with being ready to evacuate if notified.

The second channel through which storm advisories might affect fertility is contraceptive choice during an advisory. When individuals decide to engage in sexual activities, there is a probability that the usual contraceptive methods will not be readily available at home. During a low-level advisory, going out to buy a contraceptive is relatively costly due to the risk of an incoming storm. This could lead to more unplanned births.[7] During a high-level advisory, people will go out shopping for necessities anyway, so the cost of getting contraceptives is relatively low. This channel may reduce the cases of accidental conception.

A third channel through which storm advisories can affect fertility is the optimal timing and spacing of births. Parents facing a high-level advisory, on the one hand, may rationalize that their time in the near future will likely become more valuable in the aftermath of a storm due to the probable needs of rebuilding. So the opportunity cost of time spent on childbearing relative to other competing activities is high. In this case, the marginal utility of the mother's time in other activities is likely to exceed the marginal utility from having a new baby. On the other hand, parents may also think their future flow of earnings will become more uncertain in the aftermath of a storm, and they need more time to save enough to finance the increased costs of rearing a child. Both effects will lead parents to postpone childbearing, and a high-level

[6]The theoretical predictions most relevant to our paper are those from life-cycle models that predict the optimal timing of first births and optimal spacing of births. In this paper, we estimate the reduced form effects of storm advisories on fertility. The theories outlined here are used as guidance to interpret our empirical results, and we do not intend to formulate or to estimate a structural life-cycle model, such as Moffitt (1984b) and Wolpin (1984).

[7]However, people can still plan their birth through abortion after the advisory, though at a much higher cost.

advisory will exhibit a negative impact on short-term fertility.[8] It is worth pointing out that if a hurricane-stricken region experiences a rising earnings growth rate after the storm as in Belasen and Polachek (2008), the parents will be more likely to increase the time between their births.[9]

Whether storm advisories have a permanent impact on lifetime fertility will depend on how an advisory changes key long-term factors such as the parents' taste for children or the parents' life-cycle earnings profiles. If the earnings shock and relative price change resulting from a storm advisory are temporary, the fertility effect will only shift the timing of births but will not change lifetime fertility.[10] The mortality literature has termed these temporary changes in timing of events that result from catastrophic events as a "harvesting effect" (see Deschenes and Moretti 2008 and Huynen et al. 2001).

4 Data

Our data can be divided into three categories—storm advisory data, birth data, and population data. In this section, we describe the data from these categories and then detail how we put them together to estimate the fertility effect of storm advisories.

Our sample size of counties gets pared down from 164 to 47 due to the requirement of our analyses to have all three categories of data for a given county. The storm advisory data cover 164 US Atlantic Coast and Gulf Coast counties. Of the 164 coastal counties for which we have storm data, only 84 have birth data as well. Only 47 of the 84 counties that have both storm and birth data have population data as well. Therefore, our final sample of counties will be 47.

4.1 Storm advisory data

The storm advisory data come from the National Hurricane Center (NHC) of the US National Weather Service (NWS).[11] Included is information on the name of each storm, its duration, and a history of the official NWS advisories associated with each storm and their respective durations and locations. We use storm advisories from the period of 1995 to 2001 because 1995 is the earliest year of easily available storm data, and our most recent year of birth data was 2002. The storm advisory data and their collection are detailed more explicitly

[8] See Hotz et al. (1997).

[9] See Heckman and Willis (1975) and Wolpin (1984). A low-level advisory is unlikely to have the implications described in this paragraph due to its low-severity nature and its small economic impact.

[10] See Hotz et al. (1997).

[11] The data are available in rough form from the NHC web site at http://www.nhc.noaa.gov/pastall.shtml.

in Appendix A1. As very few Pacific storms ever reach the western coast of the USA, we focus on storms in the Atlantic and Gulf Coasts of the USA. Our storm advisory data cover 164 Atlantic and Gulf Coast counties. Our first decision regarding how to use the storm data was whether to use actual storm landfalls or whether to use storm advisories. We chose storm advisories for a number of reasons.[12]

Our first reason for using the storm advisory data is that we think that the information individuals first react to is the announcement of official storm projections and advisories.[13] Because of the ability of the US NWS to give advanced warnings of an impending storm along with probabilities of a hit, as well as the expected severity of the hit, individuals begin changing behavior days before a storm actually makes landfall. In fact, a storm will often change direction in such a way as to not ever affect an area that had previously been under advisory. But because a warning was issued, grocery store shelves will still have been cleared of their goods and windows will have been covered with plywood. If any fertility effect of catastrophe exists with regard to storm advisories, its effects at least begin in the time before the storm actually hits and are driven by a change in the level of uncertainty about the future. Once the storm has either missed an area or caused some devastation in an area, life either goes back to normal or people's efforts get focused in directions that may continue to affect their fertility decisions. We assume that how strong a storm is when it makes landfall and which specific areas it hits are fairly random events conditioning on the forecasting. For this reason, we focus on the storm advisory data from the NHC and not the force and location of actual hits.

The second reason for using advisory data over actual path data is that the actual storm path data only include the path of the eye of the storm in terms of latitude and longitude and selected location severity measurements. So using the actual storm landfall data as a determinant of births 9-months later would force us to make some arbitrary decisions about what area was affected by the given storm hit and whether the affected area had a constant storm severity moving outward from the eye. However, the storm advisory data include a complete listing of the severity of the advisory, the exact duration for which the advisory was in effect (in minutes), and the exact coastal boundaries of the area to which the advisory applied.

Lastly, the NHC's careful definition of advisory severity is also a major advantage of using the advisory data over the actual landfall data. The NHC defines its four levels of storm advisories as listed in Table 1. They are tropical storm watch, hurricane watch, tropical storm warning, and hurricane warning.

[12] See Appendix A2 for a detailed comparison of the storm advisory data and the actual storm path data, including a specific example of tropical storm Helene in September 2000.

[13] Conceptually, this focus on warnings and projections rather than actual storm hits is similar to the choice in macroeconomic modeling of using real-time data (forecasts) instead of revised (actual) data. The forecast data are what individuals have at that moment in time and upon which they base their decisions, whereas the revised data are only available after the fact. A good reference in this literature is Orphanides (2001).

Table 1 Definitions of storm advisory types

Tropical storm watch:	An announcement for specific coastal areas that tropical storm conditions (sustained winds within the range of 34 to 63 kt, 39 to 73 mph, or 63 to 118 km/h) are possible within 36 h.
Tropical storm warning:	A warning that sustained winds within the range of 34 to 63 kt, 39 to 73 mph, or 63 to 118 km/h associated with a tropical cyclone are expected in a specified coastal area within 24 h or less.
Hurricane watch:	An announcement for specific coastal areas that hurricane conditions (sustained winds 64 kt, 74 mph, or 119 km/h or higher) are possible within 36 h.
Hurricane warning:	A warning that sustained winds 64 kt, 74 mph, or 119 km/h or higher associated with a hurricane are expected in a specified coastal area in 24 h or less. A hurricane warning can remain in effect when dangerously high water or a combination of dangerously high water and exceptionally high waves continue, even though winds may be less than hurricane force.

Source: NHC of the US NWS

As shown in Fig. 1, these storm advisory categories can be ranked in severity along two dimensions: storm severity and probability of a storm hit. Knowing how these levels of advisories relate to each other in terms of severity is important in order to be able to interpret any results we get on estimated fertility effects of these advisories. It is clear that the lowest-level advisory is a tropical storm watch, as it has the lowest-severity storm type and storm probability. It is also clear that the highest-level advisory is a hurricane warning as it has the highest-severity storm type and storm probability.

However, it is not obvious which is the more severe advisory out of a tropical storm warning and a hurricane watch. A tropical storm warning has the lower storm type with a higher probability of a hit, while the hurricane watch has the higher storm type with a lower probability of a hit. Table 2 provides some evidence as to how these advisories should be ordered in severity. A county may be under some type of storm advisory for a continuous period of time. However, during that time, the specific types of storm advisory may change. For example, if a county spent 1 h under a hurricane watch that was then immediately upgraded to a hurricane warning that lasted for 2 h, the county would have been under 3 h of continuous storm advisories. Table 2 breaks down the storm advisory types that immediately follow each initial storm advisory type for each set of continuous sequences of storm advisories for each county in the sample period. These frequencies give some indication of how the storm advisories increase or decrease in severity.

Hurricane warnings can only be downgraded, and they are most frequently downgraded (column 4) to a tropical storm warning. Tropical storm warnings (column 2) are most likely to end a sequence of advisories, as is shown by the 632 tropical storm warnings that have no subsequent advisory. However, in cases when the tropical storm warning is modified, it is almost always upgraded

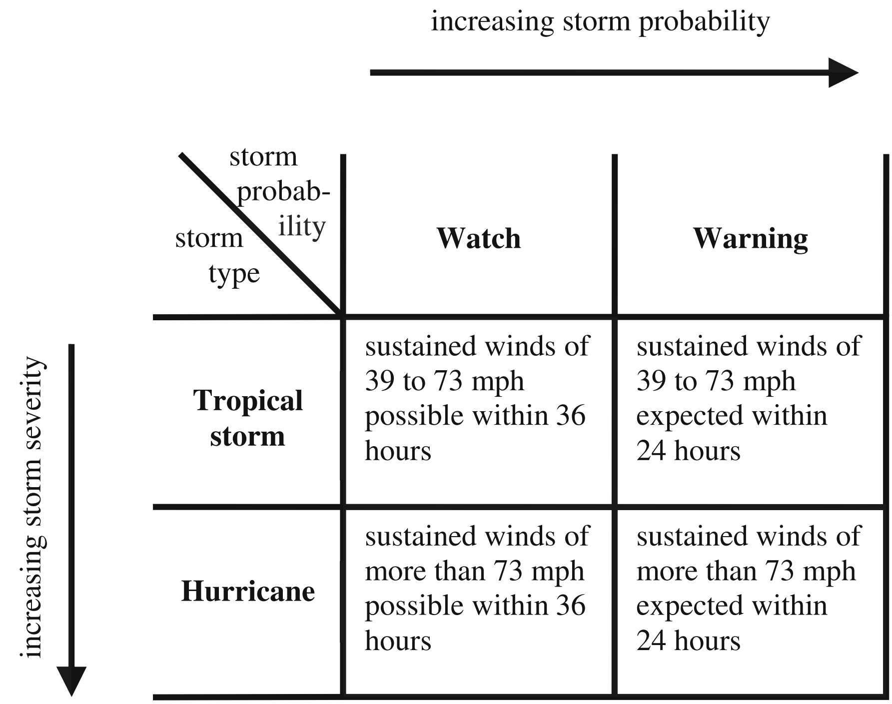


Fig. 1 Storm advisory severity matrix

to a hurricane warning. These facts suggest that tropical storm warnings should be the category consecutively lower than the maximum-severity category of hurricane warning and suggest the following storm-hit-probability severity

Table 2 Frequency of consecutive county-specific advisory type pairs by initial advisory type: 164 counties 1995–2001

Subsequent advisory type	Initial advisory type			
	Tropical storm watch	Tropical storm warning	Hurricane watch	Hurricane warning
Tropical storm watch	•	7	0	8
Tropical storm warning	191	•	168	191
Hurricane watch	24	24	•	10
Hurricane warning	14	133	232	•
No subsequent advisory	71	632	134	238
No previous advisory	285	246	476	68
Singleton advisory	56	215	108	43
Total	300	796	534	447

The values in the bottom row, entitled "Total", represent the total number of separate occurrences of the given storm advisory type across all months and all counties. It is the sum of the first five rows: Tropical storm watch + Tropical storm warning + Hurricane watch + Hurricane warning + No subsequent advisory

Table 3 Frequency of noncounty-specific storm advisories by month: 1995–2001

Advisory type	Number of advisories						
	Total	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.
Tropical storm watch	36	2	2	11	17	4	0
Hurricane watch	55	0	5	17	26	9	0
Tropical storm warning	90	2	7	30	41	10	2
Hurricane warning	45	0	6	16	17	7	0
Total	226	4	20	74	101	30	2

Source: Authors' own calculation based on data from the NHC of the US NWS

ordering: (1) tropical storm watch, (2) hurricane watch, (3) tropical storm warning, and (4) hurricane warning.

From 1995 to 2001, some level of storm advisory was given to every US county on the Atlantic or Gulf Coasts from the tip of Texas (Cameron County, Texas) to the Northern coast of Maine (Washington County, Maine). In all, we gathered storm advisory data for 164 US counties, which included 134 coastal counties and 30 slightly inland counties.[14]

In this study, we will focus on the frequency and duration of particular types of advisories as causing a fertility effect. Table 3 details the frequency of the various levels of noncounty-specific storm advisories in the US Atlantic and Gulf Coasts over the period from 1995 to 2001. The information in Table 3 is noncounty-specific in the sense that the totals are less than those of Table 2 because a single advisory can apply to multiple counties. Aggregating advisory types across counties, Table 3 shows that tropical storm warnings were the most common type of advisory, making up about 40% of all storm advisories. However, hurricane watches were the second most common, making up about 24% of the storm advisories. It is also worth noting that most of the storm advisories (77%) occurred in the August-to-September period of each year. All storm advisories in our sample occurred between June and November, as shown in Table 3.

Also of interest is the duration of storm advisories. Table 4 details these durations in similar county-specific fashion to Table 2, although we limit the county sample to the 47 coastal counties used in the analyses in Section 5.[15] Obviously, the longer an advisory lasts, the more likely it is to change the behavior of individuals. The NHC data give the duration of storm advisories in minutes. Hurricane warnings last the longest of all the storm advisories, averaging 1.1 days over the sample period. Tropical storm warnings lasted an average of about 0.9 days, and both hurricane watches and tropical storm watches lasted just over a half day on average. It is interesting to note that average duration increases with storm severity in our sample.

[14] A map of these counties is available upon request.

[15] The storm advisory relationships shown in Fig. 2 and Tables 2 through 4 are robust to changes in the size of the county sample.

Table 4 Duration (in days) of county-specific storm advisories: 47 counties, 1995–2001

Advisory type	Total advisories	Avg. duration	Std. dev.	Min.	Max.
Tropical storm watch	85	0.61	0.46	0.17	2.25
Hurricane watch	156	0.69	0.42	0.13	2.00
Tropical storm warning	259	0.85	0.48	0.13	3.13
Hurricane warning	97	1.08	0.50	0.25	2.25
Total	597	0.81	0.49	0.13	3.13

Source: Authors' own calculation based on data from the NHC of the US NWS

4.2 Birth data

The US birth data come from the National Vital Statistics System of the National Center for Health Statistics (NCHS).[16] The data we use cover births in the USA from the years 1996 to 2002, as our earliest hurricane data come from 1995 and because 2002 was the most recent birth data year available.

The NCHS birth data record information on individual births in the USA. The data are collected by NCHS from birth certificate information through cooperation among counties, states, and the national government. Included in the data are information on the date of each child's birth, the county where each birth took place, the county of residence of the mother, county population measures, an estimate of each child's gestation period length, and various demographic characteristics of the mother and father. In the analyses in Section 5, we aggregate births by county of mother's residence and by month.

Of the 1,180 counties in the 19 coastal states, we have birth data on 236 counties.[17] We do not have birth data on all counties because the NCHS groups together all birth data in a given state from counties with a population of less than 100,000. Of the 164 US coastal counties on which we have storm data, the birth sample and storm advisory sample only overlap in 84 counties (see Fig. 4). However, as we discuss later, we will only be able to use 47 of the 84 counties that have both storm and birth data because we also need to have CPS population data on each county.

Figure 2 shows the average number of monthly births in the 47 coastal US counties in our sample from 1996 to 2002, both for a given month and a given year. It is evident from the top panel that there is an upward time trend in average yearly county births across the years. The bottom panel shows the seasonal pattern in monthly county births. It is clear that most births take place in the July through October period and that the low point in monthly county births comes in February and the surrounding months. These patterns

[16]The data are available through the National Bureau of Economic Research website at http://www.nber.org/data/vital-statistics-natality-data.html.

[17]A map and list of all the counties in the 19 Atlantic and Gulf Coast States for which we have data is available upon request.

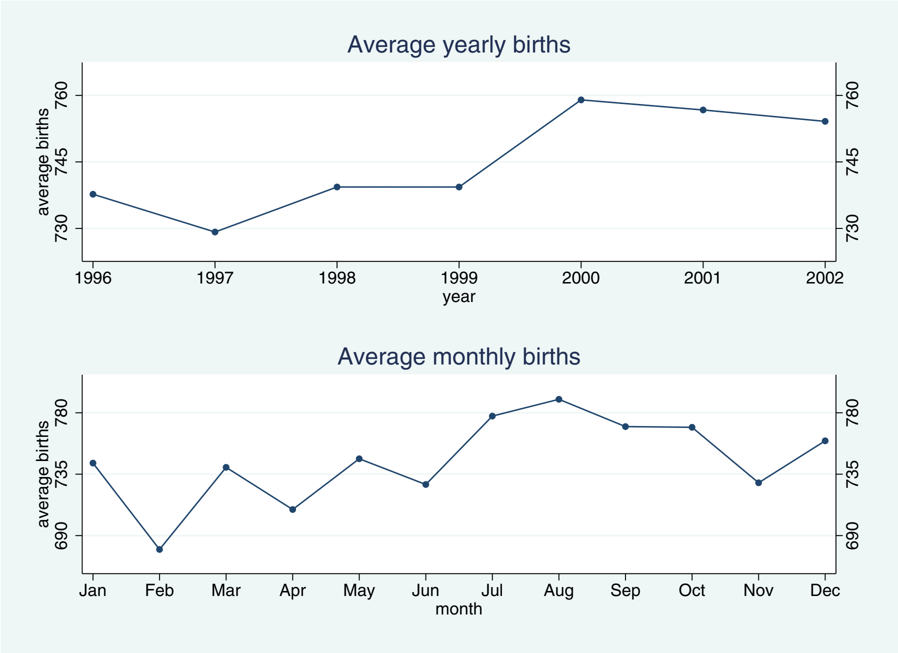


Fig. 2 Average monthly county births in Atlantic and Gulf Coasts of the USA by month and year: 47 counties, 1996–2002

also hold true when looking at all the counties in the country. We will use some of the other child and parent characteristics variables from the NCHS birth data as possible alternative outcomes to the number of births that might be affected by storm advisories.

4.3 Combining storm advisories and births

The hypothesis we are proposing in this study is that individuals change their fertility behavior when they experience an exogenous storm advisory. To test this hypothesis, we must combine the NHC storm advisory data with the NCHS birth data.

The difficulty in combining the storm advisory data and the birth data stems from the fact that neither the conception date nor the exact birth date of each child in the birth data is known. The NCHS data only give the month, year, and day of week in the birth month for each birth. The optimal method would be to record instances in which a child is conceived during a storm advisory. However, that cannot be done. In addition, we must control for those who did not change their fertility behavior (i.e., chose not to try to conceive or did not change their fertility plan from the previous month). To address these two difficulties, we aggregate the total number of births in a given county and a

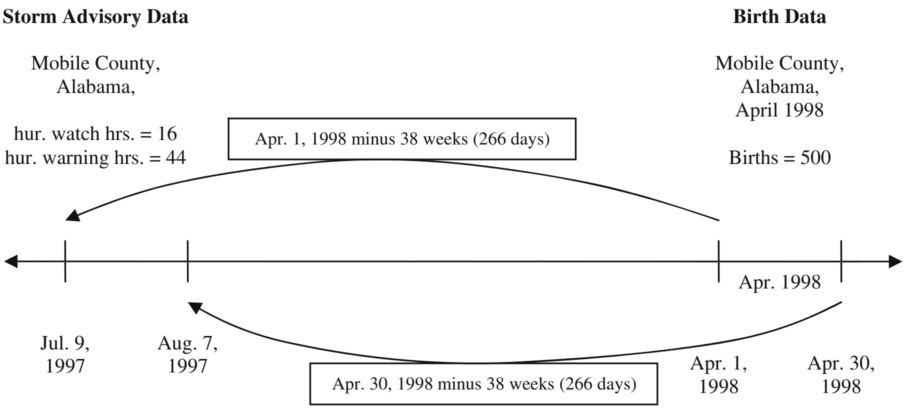


Fig. 3 Correspondence between births per month and duration of storm advisories: example Mobile County, Alabama

given month in order to test whether fertility behavior changes in response to storm advisories.

Once the births are aggregated by county and month, each observation in our birth data set becomes a county month. From the NCHS birth data, the average gestation time for a newborn child in our sample of U.S. Atlantic and Gulf Coast counties is 38.7 weeks, with a standard deviation of about 2.3 weeks—in line with the standard medical expected gestation of 38 weeks. As illustrated by Fig. 3, we measure both the instance and the intensity of storm advisories around the probable time of conception for children conceived in a given county and a given month by aggregating the number of minutes of each storm advisory type in that county in the month-long period exactly 38 weeks previous to a given county birth month. With the storm advisory data and birth data linked together in this way, we are able to measure the effect of the duration of specific types of storm advisories on fertility.[18]

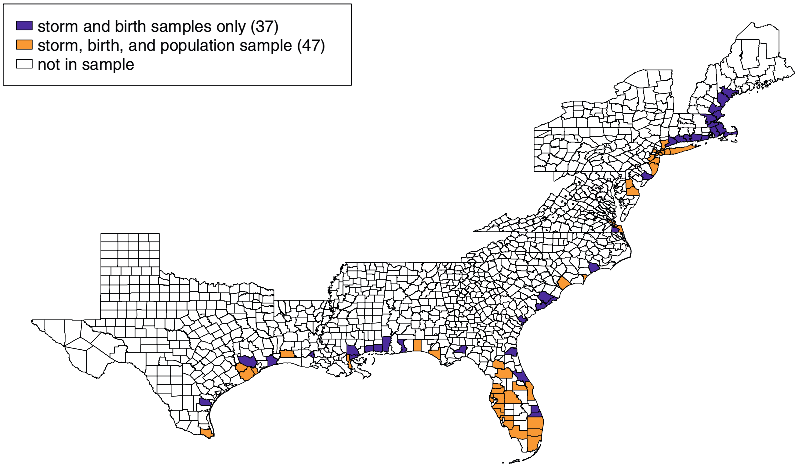
One drawback with combining the birth data and the storm data is that we have no monthly net migration data. People might migrate in the 9 months after a storm advisory, especially if a storm is particularly severe. This will affect the birth count if the mother has the child in another county after the storm advisory. Unfortunately, our data do not allow us to control for potential bias resulting from migration. However, the direction of bias is ambiguous even if there is net emigration since we do not know who migrated or whether storm migrants have a higher concentration of pregnant women. In addition, the direction of the bias may vary by storm advisory severity.

[18]We also control for the fertility effect of storm advisories with lags other than 9 months in Table 10.

4.4 County population characteristics

The NCHS birth data described in Section 4.2 have information on children actually born in the USA and on their parents. However, in order to estimate the effect of storm advisories on fertility behavior, we must also control for the county-wide demographic characteristics. First, we control for the population size of each county by using the county population variable of the mother's county of residence as a control variable in our analyses. Because the NCHS data only break county population into four categories, we include these categories as indicator variables in our estimation methods.

Second, we must observe the entire population—both those who change their fertility behavior and those who do not. We use the Current Population



Atlantic and Gulf Coast U.S. counties in storm sample and birth sample
(Bold counties are also in the population sample)

ALABAMA
Mobile

CONNECTICUT
Fairfield, New Haven, Middlesex, New London

DELAWARE
Kent, **Sussex**

WASHINGTON D.C.
Washington D.C.

FLORIDA
Alachua, Escambia, **Bay**, **Hernando**, **Brevard**, **Hillsborough**, **Broward**, **Lee**, **Charlotte**, Leon, **Collier**, **Manatee**, **Miami-Dade**, **Marion**, Duval, Martin

FLORIDA continued
Okaloosa, **Polk**, **Orange**, St. Lucie, **Palm Beach**, **Sarasota**, **Pasco**, Volusia, **Pinellas**

GEORGIA
Chatham

LOUISIANA
Calcasieu, Orleans, **Jefferson**, St. Tammany, Lafayette

MAINE
Cumberland, York

MASSACHUSETTS
Barnstable, Norfolk, Bristol, Plymouth, Essex, Suffolk, Middlesex

MISSISSIPPI
Harrison, Jackson

NEW HAMPSHIRE
Rockingham

NEW JERSEY
Atlantic, **Middlesex**, **Essex**, **Monmouth**, **Hudson**, **Ocean**

NEW YORK
Bronx, **Queens**, **Kings**, **Richmond**, **Nassau**, **Suffolk**, **New York**, **Westchester**

NORTH CAROLINA
New Hanover, Onslow

RHODE ISLAND
Washington

SOUTH CAROLINA
Berkeley, **Horry**, Charleston

TEXAS
Brazoria, Harris, **Cameron**, Jefferson, **Fort Bend**, Nueces, **Galveston**

VIRGINIA
Chesapeake City, **Norfolk City**, Portsmouth City, **Hampton City**, **Newport News City**, **Virginia Beach City**

Fig. 4 US Atlantic and Gulf Coast counties (84) in both storm and birth samples. Note: We have storm advisory data on 164 counties, of which only the 84 counties above have both storm advisory data and birth data. However, only the 47 lightly shaded counties above have storm data, birth data, and CPS population characteristics data

Table 5 Distribution of county population by county month, 1995–2001

Population category	S,B,P data[a] (47 cnt., 75 mth.)		S,B data only[b] (37 cnt., 84 mth.)		All S,B data[c] (84 cnt., 84 mth.)	
	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.
100,000 to 250,000	1,350	38.3	1,842	52.2	3,192	45.2
250,000 to 500,000	750	21.3	762	21.6	1,512	21.4
500,000 to 1 million	750	21.3	678	19.2	1,428	20.2
1 million and above	675	19.1	249	7.1	924	13.1
Total	3,525	100.0	3,531	100.0	7,056	100.0

Source: NCHS birth data

[a] Coastal counties for which we have storm data (S), birth data (B), and CPS population data (P)

[b] Coastal counties for which we have only storm data (S) and birth data (B), but no CPS population data (P)

[c] Coastal counties for which we have storm data (S) and birth data (B), regardless of whether the counties have CPS population data (P). So this category is a combination of the first two categories

Survey (CPS) for this purpose. Only 47 counties out of the 84 that had both storm data and birth data were represented in the CPS sample, as shown in Fig. 4. The CPS county population data correspond to the time period of the storm advisory data in order to control for population conditions at the time of probable child conception.

Tables 5 and 6 categorize the descriptive statistics from the CPS population characteristics into the 47 counties that have storm data, birth data, and population data; the 37 counties that have only storm data and birth data; and the 84 counties that have storm data and birth data regardless of the existence of population data. So the last group is the first group plus the second group.

From the county population distribution data in Table 5, it is clear that the counties for which we do not have CPS data have lower population density on average. Table 5 shows the distribution of county populations for our 47 counties over our 7-year period. Nearly 40% of our counties in a given month have populations of between 100,000 and 250,000.[19] However, just over 40% of the counties in a given month have populations between 250,000 and one million. Additionally, nearly 20% of our counties in a given month have populations of one million or above.

For most of the male and female statistics in Table 6, we used age ranges representing years of generally accepted positive fertility—men aged 16 and above and women between the ages of 16 and 40. We also included the county monthly births variable from the birth data for comparison.

The obvious effect in the statistics presented in Table 6 is that average monthly births in the counties with CPS population data are nearly 200 more per county on average, making the average monthly births per county in the combined average (the last two columns) nearly 100 births lower than in the

[19] For all counties in a state with a population of less than 100,000, the NCHS pools all the data into one category. So our smallest population category begins at 100,000.

Table 6 Summary statistics of CPS monthly county-specific population data by county month: 1995 to 2001

County-month variables	S,B,P data[a] (47 cnt., 75 mth.)		S,B data only[b] (37 cnt., 84 mth.)		All S,B data[c] (84 cnt., 84 mth.)	
	Mean[d]	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total monthly births[e]	746.7	738.0	564.7	822.5	655.6	786.6
Avg. age of all males	36.2	5.4	30.1	18.4	36.2	5.6
Avg. age of all females	38.8	5.3	37.8	16.6	38.8	5.5
Avg. years of education for males (age 16 and up)	13.1	0.8	11.8	2.2	13.1	0.8
Avg. years of education for females (age 16 to 40)	13.1	0.8	12.7	2.5	13.1	0.8
Percent of women married (age 16 to 40)	0.445	0.141	0.125	0.338	0.442	0.146
Unemployment rate	0.051	0.037	0.011	0.060	0.051	0.038
Avg. number of children per household	0.6	0.2			0.6	0.2
Percent white males (age 16 and up)	0.820	0.160	0.827	0.374	0.820	0.163
Percent white females (age 16 to 40)	0.761	0.179	0.882	0.297	0.762	0.180
Avg. household income	44,605	13,799			44,605	13,798

[a]Coastal counties for which we have storm data (S), birth data (B), and CPS population data (P)

[b]Coastal counties for which we have only storm data (S) and birth data (B), but no CPS population data (P)

[c]Coastal counties for which we have storm data (S) and birth data (B), regardless of whether the counties have CPS population data (P). So this category is a combination of the first two categories

[d]Mean values actually represent averages of averages because the data were first aggregated by county and month. For example, *average age of males* represents the average male age of all the monthly county average male age data points we had

[e]The total births variable comes from the NCHS birth data, not from the CPS, and corresponds to Fig. 2

more restricted sample for which we have CPS data. However, when looking at the birth rate, it is only 2% lower in the non-CPS sample, making the combined sample only 1% lower. The only other major difference is that the average age of males in counties with CPS data is about 6 years older than the average male in the coastal counties without CPS data. However, our estimation results in Section 5 do not change significantly if we leave out the CPS population controls in order to increase our sample size of counties (see Section 6).

5 Estimation

In this section, we estimate the effect of storm advisories on fertility. First, we estimate the short-term fertility effect of these advisories. That is, we estimate whether storm advisories affect the number of births 9 months after the advisory. We also test whether storm advisories affect fertility at lags other than 9 months. Then, we try to determine whether any of these fertility effects are permanent or whether they are merely transitory. Lastly, we present some results of whether there is a systematic difference between the infants conceived during an advisory and those who were not.

5.1 Fertility effect

To estimate the fertility effect of storm advisories, we use a panel data model of the form in Eq. 1. The dependent variable is the log of the number of births in a particular county i for a particular month t. The first four terms on the right-hand side of Eq. 1 are duration variables that represent the number of storm-advisory-type days for each level of storm advisory in the conception period corresponding to the birth month (as described in Section 4.3 and in Fig. 3) for a particular county. The county–month population characteristics variables from Table 6 are included in the vector $\mathbf{X}$, as well as county population dummies as shown in Table 5.[20]

$$\begin{aligned} lnbirths_{i,t} = \beta_0 + \beta_1 tswatchdays_{i,t-9} + \beta_2 hwatchdays_{i,t-9} + \beta_3 tswarndays_{i,t-9} \\ + \ldots \beta_4 hwarndays_{i,t-9} + \beta \mathbf{X}_{i,t-9} + \sum_{m=Feb}^{Dec} \gamma_m m_{t-9} + \alpha t + \theta_i + u_{i,t-9} \end{aligned} \tag{1}$$

The m_t terms represent a full set of 11 monthly indicator variables, which allow us to control for the seasonality in the birth data as evidenced in the lower

[20]We also tested a linearly interpolated county population measure taken from the US Census Bureau, and our results did not change.

Table 7 Effect of storm advisory days on the log of monthly county births nine months later: FE vs. RE (1995 to 2002)

Ind. variables[a] (duration in days)	Econometric method: Fixed effects	Random effects
Tropical storm watch	0.021[b]	0.021[b]
	(0.012)	(0.012)
Hurricane watch	0.010	0.010
	(0.008)	(0.009)
Tropical storm warning	−0.003	−0.003
	(0.006)	(0.006)
Hurricane warning	−0.022[c]	−0.022[c]
	(0.008)	(0.008)
$F(\mathrm{df}_1, \mathrm{df}_2)$	62.84	
$\chi^2(\mathrm{df})$		1,907.91
Observations	3,525	3,525
Counties (I)	47	47
Months (T)	75	75
Hausman $\chi^2(\mathrm{df})$	1.01	
Hausman p-value	1.00	

[a]Each specification also includes monthly indicator variables, a time trend, and population characteristics from the CPS as detailed in Section 4.4
[b]Significant at the 10% level
[c]Significant at the 5% level

pane of Fig. 2. We also include a time trend t to control for the increasing population growth shown in the upper pane of Fig. 2 as well. The θ_i term represents county fixed effects. We assume that the error term $u_{i,t}$ satisfies the standard assumptions of the unobserved heterogeneity model and is normally distributed.

In order to more easily interpret our results, we have changed the unit of measure of storm advisory duration from minutes to days. Therefore, the storm-advisory coefficients in our analysis represent the effect of an extra 24 h of particular types of advisories on the percentage change in a specific county's number of births 9 months later. Our results for various specifications of Eq. 1 are shown in Tables 7 and 8.

Table 7 shows our baseline specification in which all four storm-advisory types are included separately: tropical storm watches, hurricane watches, tropical storm warnings, and hurricane warnings. We test the robustness of this model by estimating it using both fixed-effects and random-effects econometric models. The Hausman specification test rejects the hypothesis that the two sets of coefficients are significantly different, so we use the random effects model in the rest of our estimations.[21]

In Table 8, we make the random-effects model with all four storm advisory types our baseline specification and also test specifications with various aggregations of the storm advisory measures. Specification 1 in Table 8 is our baseline specification. In it, we estimate the effect of each type of storm advisory separately.

[21]Fixed-effects model estimates analogous to Tables 8 through 12 are available upon request. The estimated fixed-effects model coefficients are very close to those in Tables 8 through 12, and the Hausman specification test rejects the hypothesis that the two sets of coefficients are significantly different in every case at a significance level less than 0.001.

Table 8 Random-effects estimates of storm advisory days on the log of monthly county births 9 months later: 1995 to 2002

Ind. variables[a] (duration in days)	Specification 1	2	3	4	5
Tropical storm watch	0.021[b]		0.019		
	(0.012)		(0.012)		
Hurricane watch	0.010				
	(0.009)				
Tropical storm warning	−0.003				
	(0.006)				
Hur. watch + trop. storm warning			0.002		
			(0.004)		
Hurricane warning	−0.022[c]		−0.020[d]		
	(0.008)		(0.008)		
Trop. storm watch + hur. watch		0.013[b]			
		(0.007)			
Trop. storm warning + hur. warning		−0.009[d]			
		(0.004)			
Trop. storm watch + trop. storm warning				0.004	
				(0.004)	
Hur. watch + hur. warning				−0.007	
				(0.005)	
Trop. storm watch + trop. storm warning + hur. watch + hur. warning					−0.001
					(0.003)
χ^2(df)	1,907.91	1,918.48	1,914.73	1,914.22	1,919.66
Observations	3,525	3,525	3,525	3,525	3,525
Counties (I)	47	47	47	47	47
Months (T)	75	75	75	75	75

[a]Each specification also includes monthly indicator variables, a time trend, and population characteristics from the CPS as detailed in Section 4.4
[b]Significant at the 10% level
[c]Significant at the 1% level
[d]Significant at the 5% level

The first result that stands out in Table 8 is that the estimated fertility effect from storm advisories decreases monotonically from positive to negative as advisory severity increases. This finding is strikingly robust across all specifications in both Table 8 and Table 9. In all cases, the point estimate for the fertility effect of a tropical storm or hurricane watch is positive while the effect of a tropical storm or hurricane warning is negative. For example, the interpretation of the coefficients from the baseline specification in the first column is that an extra 24 h of tropical storm watches results in an average increase in births 9 months later of just over 2.1%, and an extra 24 h of hurricane warnings results in an average decrease in births of 2.2%. Given that the average number of monthly births in our sample of coastal counties is 746, these estimated effects translate into an increase and decrease, respectively, of about 16 births 9 months later.

Also note that the estimated fertility effects are statistically significant at the severity extremes. In the first three specifications of Table 8, the

Table 9 Effect of storm advisory days on the log of monthly county births of firstborn children and non-firstborn children 9 months later: 1995 to 2002

Ind. variables[a] (duration in days)	Sample	
	Firstborn	Non-firstborn
Tropical storm watch	0.015	0.025[b]
	(0.016)	(0.015)
Hurricane watch	−0.001	0.018[b]
	(0.012)	(0.011)
Tropical storm warning	−0.005	−0.001
	(0.008)	(0.007)
Hurricane warning	−0.011	−0.028[c]
	(0.011)	(0.010)
χ^2(df)	1,169.62	1,361.48
Observations	3,525	3,525
Counties (I)	47	47
Months (T)	75	75

[a]Each specification also includes monthly indicator variables, a time trend, and population characteristics from the CPS as detailed in Section 4.4
[b]Significant at the 10% level
[c]Significant at the 5% level

low-severity and high-severity warnings are all significant.[22] We can characterize these results as conservative estimates given that our unit of observation is an entire county and that the fertility effect of a storm advisory should dissipate as one looks further inland in a county. Our findings suggest that the relationship between fertility and catastrophe is more complex than described in the media reports cited in Section 1.

Specifications 4 and 5 are important because they represent aggregations of severity that confound the effects. Statistical, as well as economic, significance is lost in both specifications. This could be one reason why studies that do not have shocks with multiple severity levels, such as Udry (1970), find no fertility effect. Severity aggregation washes out the underlying fertility effects.

As was mentioned in Section 2, Rodgers et al. (2005) found a positive fertility effect resulting from a high-severity shock—the Oklahoma City bombing. One interpretation that might harmonize these results is that catastrophes that do not result in mass evacuations, but rather force people to stay at home, have the potential for a positive fertility effect. Low-level storm advisories are generally associated with riding the storm out at one's residence, while higher-severity advisories are more associated with evacuations.

In Table 9, we perform the same regression from Table 8 specification 1, but we change the dependent variable to the log of firstborn births in a given county and the log of non-firstborn births. An interesting result emerges. Couples who have not had any children have a more inelastic demand for

[22]The coefficient on *tropical storm watch days* in specification 3 has a p value of 0.105, making it nearly significant at the 10% level.

Table 10 Random-effects estimates of storm advisory days on the log of monthly county births 9 months later by time lag: 1995 to 2002 (47 counties, 75 months, 3,525 observations)

Ind. variables[a] (duration in days)	Lag specification $t-7$	$t-8$	$t-9$	$t-10$	$t-11$	$t-12$	$t-13$	$t-14$
Tropical storm watch	0.008	0.014	0.021[b]	−0.032[c]	0.026[d]	0.020[b]	0.011	0.024[b]
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Hurricane watch	0.017[b]	0.013	0.010	0.027[c]	0.036[c]	0.003	0.018[d]	0.012
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Tropical storm warning	−0.004	−0.008	−0.003	0.006	0.007	0.005	0.002	0.001
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Hurricane warning	−0.007	−0.010	−0.022[c]	−0.026[c]	−0.015[b]	0.019[d]	0.016[b]	0.015[b]
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
χ^2(df)	1,796.27	1,870.29	1,907.91	1,968.37	1,937.52	1,932.16	1,578.25	1,553.46

[a]Each specification also includes monthly indicator variables, a time trend, and population characteristics from the CPS as detailed in Section 4.4
[b]Significant at the 10% level
[c]Significant at the 1% level
[d]Significant at the 5% level

Table 11 Random-effects estimates of storm advisory days on the log of long duration county births beginning 9 months later: 1995 to 2002

Ind. variables[a] (duration in days)	Log of long-term total births		
	5 yrs.	4 yrs.	3 yrs.
Tropical storm watch	0.004	0.011	0.001
	(0.008)	(0.012)	(0.006)
Hurricane watch	−0.001	0.004	0.009[b]
	(0.002)	(0.003)	(0.003)
Tropical storm warning	−0.000	0.001	0.001
	(0.002)	(0.003)	(0.002)
Hurricane warning	−0.001	−0.006[c]	−0.007[b]
	(0.002)	(0.003)	(0.003)
χ^2(df)	585.94	937.28	1,532.74
Observations	893	1,457	2,021
Counties (I)	47	47	47
Avg. months (T)	19	31	43

[a]Each specification also includes monthly indicator variables, a time trend, and population characteristics from the CPS as detailed in Section 4.4
[b]Significant at the 5% level
[c]Significant at the 10% level

children than those who have already had at least one child—at least in response to catastrophic shocks. On the sample of county monthly firstborn children, none of the storm advisory coefficients are either large or statistically significant, but note that the monotonically decreasing fertility effect is preserved in the point estimates. However, when using the sample of non-firstborn children, all of the coefficients become statistically significant. We conclude that most of the fertility effect comes from couples who already have at least one child. We interpret this to mean that the timing of a first child is less flexible than the timing of non-firstborn children.

5.2 Permanent fertility effect

The fertility effect described in Section 5.1 could arise from either a change in the timing of a birth or a change in total lifetime fertility. If a storm advisory only prompts individuals who were already planning to have a child to conceive either earlier or later, then the fertility effect is a transitory and short-term effect. The mortality literature refers to this short-term displacement as a "harvesting effect" (see Deschenes and Moretti 2008 and Huynen et al. 2001). However, if the storm advisory prompts individuals to increase their total number of children over their lifetime, then the fertility effect is permanent.

As shown in Eq. 1, the specifications in Table 8 use right-hand-side variables that are period $t-9$ lags, whereas log births are from period t. We also test the fertility effect of the four storm advisory categories with lags from $t-7$ to $t-14$ as shown in Table 10. Therefore, the third column of Table 10 corresponds to the first column of Table 8.

Table 12 Random-effects estimates of storm advisory days on the log of long duration county births for firstborn and non-firstborn children beginning 9 months later: 1995 to 2002

Ind. variables[a] (duration in days)	Log of long-term total births:					
	Firstborn			Non-firstborn		
	5 yrs.	4 yrs.	3 yrs.	5 yrs.	4 yrs.	3 yrs.
Tropical storm watch	0.005	0.010	–0.007	0.003	0.010	0.005
	(0.007)	(0.013)	(0.007)	(0.009)	(0.014)	(0.007)
Hurricane watch	–0.000	0.002	0.008[b]	–0.002	0.005	0.008[b]
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Tropical storm warning	–0.001	0.000	0.001	–0.000	0.002	0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
Hurricane warning	–0.002	–0.007[b]	–0.008[b]	–0.000	–0.006	–0.006[a]
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
χ^2(df)	481.24	702.85	1,121.18	590.96	920.21	1,483.45
Observations	893	1,457	2,021	893	1,457	2,021
Counties (I)	47	47	47	47	47	47
Months (T)	19	31	43	19	31	43

[a]Each specification also includes monthly indicator variables, a time trend, and population characteristics from the CPS as detailed in Section 4.4
[b]Significant at the 5% level
[c]Significant at the 10% level

The specifications for lags $t-7$ through $t-14$ in Table 10 might capture part of what is described in the mortality literature as a "harvesting effect." That is, a catastrophic event may cause an individual to either delay or accelerate something that they were going to do anyway—in this case, fertility. Table 10, in conjunction with Table 11, helps to identify whether the fertility effect is a temporary "harvesting effect" or if it is permanent.

Hurricane warnings have their most significant effect (at the 1% level) 9 and 10 months after their occurrence, causing an estimated 2.2% and 2.6% decline in births, respectively, 9 and 10 months after the warning. Tropical storm warnings in Table 10 have no estimated fertility effects that are significant at even the 10% level. Hurricane watches have their greatest effect 10 and 11 months after the watch was issued, causing an estimated 2.6% and 3.7% increase in monthly births, respectively, 10 and 11 months after the watch was issued. The coefficients on tropical storm watches are all positive, except for the highly significant negative effect measured in the 10-month lag specification.

We also test whether the fertility effect of storm advisories is permanent or transitory by estimating a random-effects model with the same independent variables as in Eq. 1 but with the dependent variable being the log of total births in a county for a rolling period of a certain long-term duration. Table 11 shows the estimated coefficients on the four storm-advisory types on births for 3, 4, and 5 years starting 9 months after the storm advisory. In this test, coefficients on storm advisory types that are not significantly different from zero provide evidence that any fertility effects measured in Tables 8 and 10 are merely "harvesting effects" in which planned births were merely either delayed or accelerated.

A weakness of the ability of our approach to identify permanent fertility effects is that we only have 6 years of data. Therefore, our 3- to 5-year rolling windows greatly reduce the time dimension of our panel, and thereby reduce our ability to identify permanent effects.

In the 3-year specification, hurricane watches and hurricane warnings have a nearly equal and opposite long-run fertility effect that is significant at the 10% level—hurricane watches increase a county's births by just under 1% over the following 3-year period and hurricane warnings decrease the county births by about the same percentage. The pattern is similar over the 4-year horizon, but expectedly dissipates over the 5-year horizon.[23] In Table 12, we separate the sample into county first births and county non-first births, and we find no material differences from the total births permanent effects in Table 11.

In summary, we have weak evidence that hurricane warnings have a negative long-term fertility effect. This result is similar to but considerably weaker than the findings of Lindstrom and Berhanu (1999), Pörtner (2008), and

[23] We do not show the 1- and 2-year horizons because parents must wait at least 9 months to have another child and often wait more than that. Therefore, the 1- and 2-year horizons predictably show an opposite pattern of the results from the 3- and 4-year specifications in Table 11.

Rodgers et al. (2005), all of whom find a significant long-term fertility effect as well. Similar to the trauma of surviving a high-severity storm, a terrorists attack or famine and war are likely to have profound impacts on people physically and mentally and are likely to permanently alter their taste for children. Other things equal, a catastrophe will also be likely to have a larger and more long-term effect on the fertility behavior of individuals in low income economies without functioning insurance markets because fertility is unlikely to be used as an insurance mechanism to smooth the risk in developed countries such as the USA.

5.3 Characteristics of newborns and their parents

If a fertility effect from storm advisories does exist, as we have found in this section, then knowing something about the parents of these children born after

Table 13 Means (and standard deviations) of individual characteristics from birth sample by whether or not conceived under storm advisory: 47 counties, 1996 to 2002

Individual characteristic	Whole sample	Conceived during advisory	Not conceived dur. adv.
Newborns			
Gestation period in weeks	38.74 (2.68)	38.71 (2.73)	38.74 (2.67)
Percent male	0.5121 (0.4999)	0.5116 (0.4999)	0.5121 (0.4999)
Birthweight in grams	3,280.4 (610.5)	3,285.7 (615.5)	3,280.0 (610.1)
Children per birth (twins, etc.)	1.035 (0.197)	1.034 (0.195)	1.035 (0.197)
Apgar score (range: 1 – 10)	8.964 (0.711)	8.947 (0.731)	8.965 (0.710)
Percent Firstborn	0.420 (0.494)	0.414 (0.492)	0.420 (0.494)
Mothers			
Mother's age in years	27.96 (6.30)	27.74 (6.26)	27.97 (6.30)
Hispanic mothers	0.261 (0.439)	0.232 (0.422)	0.263 (0.440)
White mothers	0.684 (0.465)	0.707 (0.455)	0.683 (0.465)
Mother's education in years	12.88 (2.81)	12.91 (2.73)	12.87 (2.82)
Married mothers	0.624 (0.485)	0.634 (0.482)	0.623 (0.485)
Fathers			
Father's age in years	31.46 (7.01)	31.26 (6.97)	31.48 (7.01)
Hispanic fathers	0.242 (0.428)	0.209 (0.406)	0.244 (0.429)
White fathers	0.725 (0.447)	0.749 (0.434)	0.723 (0.447)

storm advisories would tell us which groups are affected more or less by this type of shock. It is also interesting to compare the characteristics of infants conceived during an advisory to the ones not conceived during an advisory.

As we described in Section 4.2, the NCHS birth data record information on the mother, father, and baby, in addition to the fact that the child was born. We tabulated the means and standard deviations of those individual characteristics by various groupings. These tabulations are in Tables 13 and 14. Table 13 divides the parents into two groups—those who gave birth to a child conceived during a storm advisory and those who gave birth to a child who was not conceived during an advisory. Table 14 further divides those parents who gave birth to a child conceived during an advisory into four groups according to the severity of the advisory. The two tables show that there is no systematic difference between the infant's characteristics, such as

Table 14 Means (and standard deviations) of individual characteristics from birth sample by type of storm advisory conceived under: 47 counties, 1996 to 2002

Individual characteristic	Conceived during:			
	Trop. storm watch	Hurricane watch	Trop. storm warning	Hurricane warning
Newborns				
Gestation period	38.74	38.69	38.71	38.72
in weeks	(2.74)	(2.74)	(2.72)	(2.77)
Percent male	0.5119	0.5122	0.5112	0.5111
	(0.4999)	(0.4999)	(0.4999)	(0.4999)
Birthweight	3,292.9	3,285.8	3,285.9	3,295.4
in grams	(612.9)	(617.8)	(615.6)	(616.8)
Children per birth	1.035	1.032	1.034	1.031
(twins, etc.)	(0.196)	(0.189)	(0.194)	(0.184)
Apgar score	8.934	8.931	8.944	8.918
(range: 1 – 10)	(0.722)	(0.733)	(0.730)	(0.705)
Percent	0.412	0.412	0.413	0.415
firstborn	(0.492)	(0.492)	(0.492)	(0.493)
Mothers				
Mother's age	27.83	27.48	27.77	27.18
in years	(6.28)	(6.23)	(6.28)	(6.22)
Hispanic mothers	0.226	0.217	0.233	0.220
	(0.418)	(0.412)	(0.423)	(0.414)
White mothers	0.705	0.707	0.711	0.741
	(0.456)	(0.455)	(0.453)	(0.438)
Mother's education	12.95	12.89	12.92	12.86
in years	(2.75)	(2.68)	(2.73)	(2.63)
Married mothers	0.637	0.631	0.635	0.641
	(0.481)	(0.483)	(0.482)	(0.480)
Fathers				
Father's age	31.32	31.04	31.28	30.71
in years	(6.97)	(6.98)	(6.99)	(6.99)
Hispanic fathers	0.202	0.194	0.208	0.197
	(0.401)	(0.395)	(0.406)	(0.397)
White fathers	0.745	0.754	0.752	0.788
	(0.436)	(0.430)	(0.432)	(0.409)

gestation period, gender, birth-weight, and Apgar score,[24] no matter whether an infant is conceived during an advisory or not, or conceived during different severity of advisory.[25] From the standard deviations in Tables 13 and 14, it is clear that a standard t test rejects that the means for any category across different conception circumstances are statistically different from each other. The biggest difference, however, seems to be that the percent of firstborn children in Table 13 conceived during a storm advisory is slightly less than the percent of firstborn children not conceived during a storm advisory.

For the parents' characteristics, the only notable difference is between characteristics categories in the race variables. Hispanic mothers and fathers are less likely to conceive a child during an advisory and are less likely to conceive a child during a hurricane watch, which is the highest level of advisory. However, these findings are not statistically significant.

6 Robustness

6.1 Estimation without CPS population controls

One potential drawback of the estimated coefficients from Table 8 is that the sample size of counties in the panel is reduced to 47 because of the sparse number of counties for which we obtained CPS population data. For this reason, we ran the same regressions without the CPS population controls in order to make sure that the results are robust when using the larger sample of 84 countries for which we have both storm and birth data. The estimation results are presented in Table 15.

Our main conclusion from Table 15 is that the monotonically decreasing fertility effect from positive to negative is also prominent when the CPS population controls are excluded. The added observations reduce standard errors making more of the coefficients statistically significant at a higher level. However, one change is that the estimated negative fertility effect from tropical storm warnings is as big as, and more statistically significant than, that of a hurricane warning.

A comparison of the regression results with the full sample not controlling for CPS population characteristics in Table 15 with the estimates that restrict the sample to counties with CPS population data in Table 8 show that the broad

[24]The Apgar score is an assessment of a newborn's adjustment to life immediately after birth. Five criteria are evaluated: heart rate, breathing rate, reflexes, muscle tone, and color. The child is scored at 1 and 5 min after birth. See Apgar (1953).

[25]Angrist and Evans (1999) and Pop-Eleches (2006) argue and show that unplanned birth can conflict long-term educational and labor market plans of a mother, which can result in a negative effect on the child. Our results here cannot be used to test whether the babies conceived during an advisory are likely to be unplanned births or not since realization of the effect in Angrist and Evans (1999) and Pop-Eleches (2006) takes time.

Table 15 Random-effects estimates of storm advisory days on the log of monthly county births nine months later without CPS population controls: 1995 to 2002

Ind. variables[a] (duration in days)	Specification				
	1	2	3	4	5
Tropical storm watch	0.020[b]		0.017[c]		
	(0.009)		(0.009)		
Hurricane watch	0.004				
	(0.007)				
Tropical storm warning	−0.011[d]				
	(0.004)				
Hur. watch + trop. storm warning			−0.007[b]		
			(0.003)		
Hurricane warning	−0.011[b]		−0.009[c]		
	(0.005)		(0.005)		
Trop. storm watch + hur. watch		0.010[c]			
		(0.006)			
Trop. storm warning + hur. warning		−0.012[d]			
		(0.003)			
Trop. storm watch + trop. storm warning				−0.003	
				(0.003)	
Hur. watch + hur. warning				−0.006[c]	
				(0.003)	
Trop. storm watch + trop. storm warning + hur. watch + hur. warning					−0.005[b]
					(0.002)
χ^2(df)	2,534.94	2,533.81	2,531.04	2,524.32	2,524.17
Observations	7,056	7,056	7,056	7,056	7,056
Counties (I)	84	84	84	84	84
Months (T)	84	84	84	84	84

[a]Each specification also includes monthly indicator variables, a time trend, and county population dummies as in Table 5
[b]Significant at the 5% level
[c]Significant at the 10% level
[d]Significant at the 1% level

sample estimates are more precisely measured, that the negative fertility effect of a hurricane warning is diminished, and that the negative effect of a tropical storm warning is increased. The cause of this difference is the lower birthrate and the lower average age of males. However, the changes in the coefficients and implications from Table 15 do not change significantly from Table 8.

6.2 Fertility effect estimation with inland counties

Our analyses in Section 5 use only coastal counties in the Atlantic and Gulf Coast states because our estimates focus on the effect of storm advisories on fertility. The counties further inland in the coastal states provide no valuable information on these estimates because they have no storm advisories and provide no variation along that dimension. The inland counties would be helpful in refining the estimates on the CPS population control variables.

Table 16 Random-effects estimates of storm advisory days on the log of monthly county births 9 months later with inland counties included: 1995 to 2002

Ind. variables[a] (duration in days)	Specification 1	2	3	4	5
Tropical storm watch	0.014		0.011		
	(0.012)		(0.012)		
Hurricane watch	0.001				
	(0.009)				
Tropical storm warning	−0.011[b]				
	(0.006)				
Hur. watch + trop. storm warning			−0.007		
			(0.004)		
Hurricane warning	−0.028[c]		−0.026[c]		
	(0.009)		(0.008)		
Trop. storm watch + hur. watch		0.005			
		(0.007)			
Trop. storm warning + hur. warning		−0.016[c]			
		(0.005)			
Trop. storm watch + trop. storm warning				−0.004	
				(0.004)	
Hur. watch + hur. warning				−0.014[c]	
				(0.005)	
Trop. storm watch + trop. storm warning + hur. watch + hur. warning					−0.009[c]
					(0.003)
χ^2(df)	3,841.81	3,838.28	3,835.02	3,834.92	3,834.48
Observations	8,683	8,683	8,683	8,683	8,683
Counties (I)	116	116	116	116	116
Avg. months (T)	74.9	74.9	74.9	74.9	74.9

[a]Each specification also includes monthly indicator variables, a time trend, and county population dummies as in Table 5
[b]Significant at the 10% level
[c]Significant at the 1% level

Table 16 presents the estimates from the specifications shown in Table 8 with the inland counties included. The signs of the estimated effects are fairly similar to those from Table 8, although the statistical significance of the estimates changes quite a bit. The incorporation of all the inland counties does not change our basic results.

7 Conclusion

Using rich panel data with a large sample of multiple-severity shocks, we measure the fertility effect of storm advisories for counties along the Atlantic and Gulf coasts of the USA. We test for short-term fertility effects over many different time horizons including various lags other than 9 months, as well as over periods much longer than 1 month. Our findings suggest that the relationship between fertility and catastrophe is more complex than described in the media.

We find that a positive and significant fertility effect is associated with the lowest level of storm advisory: tropical storm watches. However, we find that the estimated fertility effect decreases monotonically from positive to negative as the storm advisory severity increases. A significant negative fertility effect is associated with the most severe advisory level: hurricane warnings.

In addition, we find that most of this fertility effect, both with low and high severity advisories, comes from couples who have had at least one child previously. This suggests that the elasticity of demand for children is relatively inelastic for first children but becomes more elastic after couples have their first child.

We also test whether this negative effect is transitory or permanent, and our study provides slight evidence that the fertility effect of hurricane warnings has a long-term effect on the number of births in a county. Lastly, when comparing the infants conceived during an advisory to the ones who were not, we find that their characteristics are not systemically different, and neither are those of their parents.

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Appendix

A1 Storm advisory data description

Our storm advisory data come from the NHC of the US NWS. The data were taken from the NHC web site at http://www.nhc.noaa.gov/pastall.shtml. The NHC has readily available information on each named storm from 1995 on. The information on storms before 1995 is more sparse. Our storm data only cover the period from 1995 to 2001 because the data before 1995 were not posted publicly and we do not have birth data beyond 2002. However, the NHC storm data are usually up-to-date up to 1 month previous to the current date.

Included in the NHC's summary of each named storm is a table entitled some variant of "watch and warning summary" (See Table 17 in Appendix A2). The watch and warning summary tables list the date and time in which an advisory was issued, the type of advisory, and the geographic area to which the advisory applied.

One problem with these tables is that the geographic range of a specific advisory is often described in terms of cities or geographic features rather than affected counties. Therefore, an important step in gathering these data was carefully going through each storm advisory description in the watch and warning summary tables and mapping them into affected counties. In

Table 17 Watch and warning summary, tropical storm Helene, September, 2000

Date/time (UTC)	Action	Location
16/0300	Tropical storm watch issued	St. Maarten, Saba, St. Eustatius
16/0900	Tropical storm watch issued	Antigua, Anguilla, Barbuda, Montserrat, Nevis, St. Kitts
16/1700	Tropical storm watch discontinued	St. Maarten, Saba, St. Eustatius, Antigua, Anguilla, Barbuda, Montserrat, Nevis, St. Kitts
20/0300	Tropical storm warning issued	Cuban provinces of Isle of Youth, Havana, Pinar Del Rio, and the city of Havana
20/1500	Tropical storm warning discontinued	Cuban provinces of Isle of Youth, Havana, Pinar Del Rio, and the city of Havana
21/1500	Tropical storm warning issued	The mouth of the Pearl River on the Louisiana-Mississippi border eastward to the mouth of the Aucilla River, Florida
21/2100	Hurricane watch issued	The Florida-Alabama border eastward to the mouth of the Aucilla River, Florida
22/0300	Tropical storm warning discontinued	The mouth of the Pearl River on the Louisiana-Mississippi border eastward to west of Pascagoula, Mississippi
22/0900	Hurricane watch discontinued	The Florida-Alabama border eastward to the mouth of the Aucilla River, Florida
22/1500	Tropical storm warning discontinued	Pascagoula, Mississippi eastward to just west of Destin, Florida
22/1800	Tropical storm warning discontinued	Destin, Florida eastward to the mouth of the Aucilla River, Florida

This table corresponds to Table 3 on the NHC website page for tropical storm Helene, 2000, http://www.nhc.noaa.gov/2000helene.html#FIG1

doing this, we found that the geographical and city descriptions almost always corresponded to county boundaries.

Although tropical storms and hurricanes can affect inland areas, we chose to focus only on coastal counties. However, we did include some “slightly inland” counties in our study. These “inland” counties are not separated from the coast by more than one county and, for the most part, come from the Houston and New Orleans areas. Their inclusion in the study comes from their membership in a large coastal metropolitan statistical area that is often the recipient of the storm advisories studied in this paper. In the broad sample of 164 counties for which we had storm advisory data, 30 counties were characterized as being “slightly inland.” (A map of the counties in the hurricane sample that highlights those designated as slightly inland is available upon request.) Of the subsample of 84 counties for which we had both birth data and storm advisory data, only 14 were “slightly inland.”

A2 Storm hit data vs advisory data

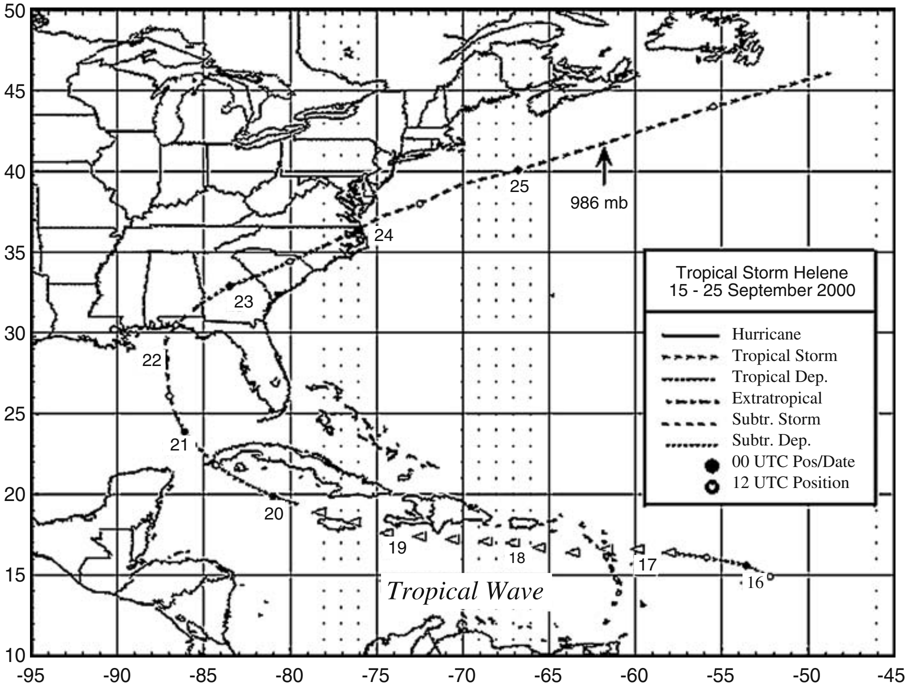
The broad question of this study is how catastrophic events such as hurricanes affect fertility. Our initial expectation was to carry out the analysis using actual storm hit data. However, we quickly discovered that the storm hit data were not only more difficult to use, but they were also lacking in a few areas. We decided that using the storm advisory data was superior to the actual hit data in both their usability and their capability of identifying the effects we were after. In this appendix, we detail the reasons for using storm advisory data over storm hit data and give a comparison of the two.

As discussed in Section 4.1, we chose to use the storm advisory data because these capture more of the effect of storms. The ability of the NWS to track and forecast storms is such that the reaction of individuals to a hurricane warning may not be much different from the reaction to an actual hit. The ex ante effect of storm advisories is certainly more broad and may also subsume much of the ex post effect of an actual storm hit. The information to which individuals first react is the advisory. In addition, the storm landfall data only include the path of the eye of the storm in terms of latitude and longitude, the data of which are difficult to translate into the county unit of account. Lastly, in addition to storm severity, the storm advisory data provide the added dimension of the probability of a storm hit. This gives us the added dimension of risk in our dataset.

We illustrate the comparison between storm advisory data and storm hit data using Tropical Storm Helene from September 15 to 25, 2000. (The data on Tropical Storm Helene can be found on the National Hurricane Center website at http://www.nhc.noaa.gov/2000helene.html#FIG1.) We generated the storm advisory data used in this paper from entries like Table 17, following the methodology described in Appendix A1. This table gives the advisory type, duration, and counties covered with great detail. The locations listed in the last column correspond to county boundaries. For example, the counties that correspond to the location covered by the tropical storm warning issued on September 21, at 3:00 p.m., are Hanock, Harrison,and Jackson Counties in Mississippi; Mobile and Baldwin Counties in Alabama; and Escambia, Santa Rosa, Okaloosa, Walton, Bay, Gulf, Franklin, Wakulla, and Jefferson Counties in Florida.

Figure 5 and Table 18 give the actual storm path data. These data show that tropical storm Helene reached its peak wind speeds of near the 63-kt minimum speed defined as hurricane force in the 30 h before it made landfall in the panhandle of Florida on September 22 around noon (see Table 1 for definitions of storm types). Once reaching land, Helene weakened to a tropical depression until it crossed through North Carolina from about 6:00 p.m. on September 23 until 12:00 a.m. on September 24, when Helene's wind speeds reached back up to 60 kt.

Notice from Table 17 that a hurricane watch was issued for all the coastal panhandle counties in Florida on September 21 at 9:00 p.m. and was discontinued at 9:00 a.m. the next morning. From Table 18, it is clear that tropical storm Helene never strengthened to a hurricane, but it is likely that the residents of the panhandle counties who received the hurricane watch acted differently from the residents in the broader set of counties who were under the tropical storm warning.



Source: National Hurricane Center and National Oceanic and Atmospheric Administration web site (http://www.nhc.noaa.gov/2000helene.html#FIG1).

Fig. 5 Best track positions for tropical storm Helene, 15–25 September 2000

Also note that the initial tropical storm warning extended from the Florida panhandle counties all the way to the Mississippi–Louisiana border. How would the effect of the storm on those counties be measured if the econometrician were only using the storm path data? That is, given that the eye of the storm passed through Okaloosa County, Florida, should the two adjacent counties be included as being affected or should the affected counties be broader? This illustrates a major problem with the storm path data. How wide a band around the actual path should be affected? Experience has shown that large storms can affect a large coastal area, even if the eye of the storm only hits one coastal county. This example shows that creating storm hit data from storm path data (this is the only readily available data source) will necessarily invoke arbitrary judgment and measurement error. If a classical independent measurement error is assumed, then one will underestimate the fertility effect of hurricane. Hurricane advisory data used in our paper can also be treated as a measurement for the actual hurricane hit but with measurement error; the estimated fertility effects we present here are also likely to be underestimated.

Table 18 Best track for tropical storm Helene, 15–25 September 2000

Date/Time (UTC)	Position Lat.(° N)	Lon.(° W)	Pressure (mb)	Wind Speed (kt)	Stage
15/1200	14.9	52.2	1010	25	Tropical depression
15/1800	15.3	53.0	1010	25	Tropical depression
16/0000	15.6	53.6	1010	25	Tropical depression
16/0600	15.8	54.4	1010	25	Tropical depression
16/1200	16.1	55.9	1010	30	Tropical depression
16/1800	16.4	58.0	1010	30	Tropical wave
17/0000	16.6	59.9	1010	30	Tropical wave
17/0600	16.6	61.7	1010	30	Tropical wave
17/1200	16.4	63.6	1010	30	Tropical wave
17/1800	16.7	65.6	1010	30	Tropical wave
18/0000	17.0	67.1	1010	30	Tropical wave
18/0600	17.1	68.7	1010	30	Tropical wave
18/1200	17.2	70.6	1010	30	Tropical wave
18/1800	17.4	72.5	1010	30	Tropical wave
19/0000	17.6	74.4	1010	30	Tropical wave
19/0600	18.3	76.3	1010	30	Tropical wave
19/1200	18.9	78.3	1010	30	Tropical wave
19/1800	19.4	79.6	1010	30	Tropical depression
20/0000	19.9	81.0	1010	30	Tropical depression
20/0600	20.7	82.6	1010	25	Tropical depression
20/1200	21.8	84.3	1010	25	Tropical depression
20/1800	23.0	85.4	1010	25	Tropical depression
21/0000	23.9	86.1	1008	25	Tropical depression
21/0600	24.9	86.6	1007	35	Tropical storm
21/1200	26.1	87.0	1006	45	Tropical storm
21/1800	27.1	87.1	999	60	Tropical storm
22/0000	28.4	87.2	996	60	Tropical storm
22/0600	29.5	87.2	1001	50	Tropical storm
22/1200	30.5	86.6	1006	35	Tropical storm
22/1800	31.6	85.4	1010	25	Tropical depression
23/0000	32.9	83.5	1011	25	Tropical depression
23/0600	33.6	81.7	1012	25	Tropical depression
23/1200	34.4	80.0	1011	25	Tropical depression
23/1800	35.4	78.0	1010	35	Tropical storm
24/0000	36.4	76.1	1008	40	Tropical storm
24/0600	37.2	74.7	1005	45	Tropical storm
24/1200	38.0	72.5	1001	45	Tropical storm
24/1800	39.2	70.1	997	45	Tropical storm
25/0000	40.1	66.8	993	55	Tropical storm
25/0600	41.6	62.2	986	60	Tropical storm
25/1200	44.0	55.5	988	55	Tropical storm
25/1800	46.1	48.8	990	45	Tropical storm
26/0000					Absorbed by a front
25/0600	41.6	62.2	986	60	Minimum pressure
22/1200	30.5	86.6	1006	35	Landfall near Fort Walton Beach, FL

This table corresponds to Table 1 on the NHC website page for tropical storm Helene, 2000, http://www.nhc.noaa.gov/2000helene.html#FIG1

However, one weakness of the storm advisory data, at least in the case of tropical storm Helene, is that no advisories were given in Table 17 after September 22 at 6:00 p.m. even though the storm strengthened back to tropical storm force late on September 23 as it passed through North Carolina. This incongruity is not common in the data, and it does not overcome the benefits of the storm advisory data.

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