The Fertility Effect of Catastrophe: Myth or Measurable

Richard W. Evans
University of Texas at Austin
evans@eco.utexas.edu

Yingyao Hu
University of Texas at Austin
hu@eco.utexas.edu

DRAFT
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Abstract

For years, anecdotal evidence has suggested increased fertility rates resulting from catastrophic events in an area. We attempt to measure this fertility effect using hurricane data and fertility data for the Atlantic and Gulf-coast counties of the United States. We find that low-level storm advisories, such as tropical storm watches and hurricane watches, produce a positive jump in a county's birth rate nine months later. However, higher severity advisories, such as tropical storm warnings and hurricane warnings, produce a negative fertility effect nine months later. The fact that the sign of the fertility effect changes with the severity of the advisory may be an indication as to why previous studies have found no positive fertility effect of catastrophe.

1 Introduction

For years, the press have reported anecdotal evidence of a positive fertility effect resulting from catastrophic events in an area. However, until recently, the results of studies trying to measure these effects have been either inconclusive or they have found the opposite effect. Our aim in this study is to quantify the fertility effect of catastrophes using U.S. hurricane data from 1995 to 2001 and U.S. birth data from 1996 to 2002. Using a fixed-effects econometric model, we find that low-severity storm advisories are associated with a positive fertility effect while higher-severity advisories have nearly equal and opposite negative effect. As the type of advisory goes from least severe to most severe, the fertility effect of the specific advisory type decreases nearly monotonically.

The main contributions of this study are its use of exogenous storm advisory shocks over a significant time period, its large sample area of U.S. counties, and the variance in severity of the shocks. Until recently, previous attempts to measure the fertility effect of a catastrophe have used only single shock natural experiments that observe only a single area (usually a county). But all previous studies use only a single catastrophic event so that they observe no variance in severity. Using our rich storm advisory data in combination with U.S. county birth data, we are able to more accurately measure the fertility effect of catastrophes.

The idea is that rational agents change their fertility decisions when they experience an exogenous shock—in this case, a tropical storm or a hurricane. The structural reason for this change is not clear to us at this point, nor is it within the scope of this paper to propose a theoretical model to explain why agents change their behavior and through what channel. However, we can propose some intuitive possibilities.

In the first case, individuals could change their reproductive behavior before a storm arrives. This pre-storm advisory channel is the focus of our study. Because of the ability of the U.S. National Weather Service to give advanced warnings to areas of impending storm along with probabilities of a hit as well as severity of the hit, individuals begin changing behavior days before a storm actually hits. In fact, many times a storm will change direction and not ever affect an area. But because a warning was issued, grocery store shelves still will have been cleared of their goods. On the other hand, individuals may change their behavior after a traumatic event such as a storm.

The seminal paper in this literature is Udry (1970). He studies the great New York City black out of November 9, 1965, in which the city lost electrical power for up to 10 hours. Nine months after the power outage, Tolchin (August 10, 1966) reports in *The New York Times* that several local hospitals had reported record high single-day births—in some cases, setting record highs.

Using daily number of births data from the New York City Health Department for the years 1961 to 1966, Udry (1970) assumes that 90 percent of babies conceived on the date of the blackout would be born within a three-week range centered 266 days (38 weeks) from the date of the blackout. Calculating the mean births for the same three-week period in the previous years, Udry creates 95-percent confidence intervals and finds that the increase in New York City births nine months after the blackout were not more than two standard deviations greater than the previous years' mean. Using this simplistic procedure, he concluded that there was no positive fertility effect resulting from the black out.

More recently, Rodgers, John & Coleman (2005) estimate the effect on fertility rates of the Oklahoma City bombing. They find a positive fertility effect for the area immediately surrounding Oklahoma City nine months after the bombing. They propose that these analyses would equally apply to events such as the September 11, 2001 attacks in the United States and to hurricane.

The primary weakness of the studies by Udry (1970) and Rodgers, John & Coleman (2005) is that they only have one shock and, therefore, have no variance in the severity of the shock. The more recent study by Rodgers, John & Coleman (2005) is a step forward because they look at time series for a number of counties controlling for county and time specific characteristics. But the two studies find conflicting results.

As with the New York City black out of 1965, the Oklahoma City bombing of 1995, and the terrorist attacks of September 11, 2001, the press have reported increased birth rates nine 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.

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 and sociological literature. 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.

In our study, we choose to try to measure the fertility effect of catastrophe using hurricane data. U.S. storm advisory data represents 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.

We undertook this study because of the attractiveness of the U.S. hurricane and population data as well as the renewed reports of baby booms following the increased number of hurricanes hitting the Atlantic and Gulf coasts of the United States. We find that low-level storm advisories, such as tropical storm watches and hurricane watches, in a county do have a positive effect on the fertility rate of that county nine months later. However, as the warning severity increases, as with tropical storm warnings and hurricane warnings, the fertility effect changes sign and becomes negative.

2 Data

Our data can be divided into two main sources—hurricane data and birth data. In this section, we describe the hurricane data and the birth data and then detail how we put them together.

2.1 Hurricane data

The hurricane data come from the National Hurricane Center (NHC) of the United States National Weather Service (NWS).[1] Included is information on the name of each storm, its duration, as well as a history of the official NWS advisories and their respective durations and locations. We use storm advisories from the period of 1995 to 2001, as 1995 is the earliest year of easily available hurricane data and our most recent year of birth data is 2002. The hurricane data and their collection are detailed more explicitly in Appendix A-1. As very few Pacific storms ever reach the western coasts of the United States, we focus on storms in the Atlantic and Gulf Coasts of the United States. Our first decision regarding this data was whether to use actual storm landfalls or whether to use storm advisories. We chose storm advisories for a number of reasons.

Our first reason for using the storm warning data is that we think that if any positive fertility effect of catastrophe exists with regard to hurricanes, it is caused in the time before the storm actually hits and is 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 other than fertility decisions. We assume that how strong a hurricane is when it makes landfall and which specific areas it hits are fairly random events. The information that individuals really act upon is the announcement of official hurricane projections and warnings. For this reason, we focus on the storm warning data from the NHC and not the force and location of actual hits.[2]

The actual hurricane landfall 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 nine-months later would force the researcher to make some *ad hoc* decisions about area was affected

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[1] The data are available from the NHC web site at `http://www.nhc.noaa.gov/pastall.shtml`.

[2] This focus on warnings and projections rather than actual hurricane hits is similar to the choice in macroeconomic modeling of using real-time data (forecasts) instead of revised (actual) data. The forecast data is what individuals have at that moment in time, whereas the revised data is only available after the fact.

by the given storm hit and whether the affected area had a constant storm severity moving outward from the eye. The storm advisory data includes 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.

The NHC's careful definition of advisory severity is also 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.

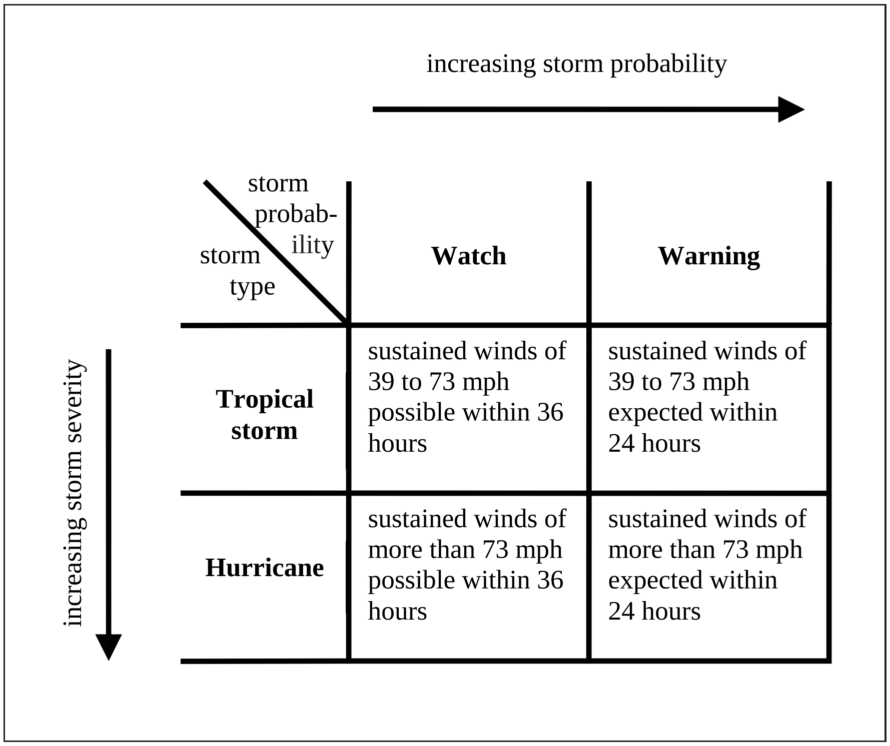
Table 1: Definitions of Storm Advisory Types

Tropical storm watch:	An announcement for specific coastal areas that tropical storm conditions (sustained winds within the range of 34 to 63 kt, 39 to73 mph, or 63 to 118 km/hr) are possible within 36 hours.
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/hr associated with a tropical cyclone are expected in a specified coastal area within 24 hours or less.
Hurricane watch:	An announcement for specific coastal areas that hurricane conditions (sustained winds 64 kt, 74 mph, or 119 km/hr or higher) are possible within 36 hours.
Hurricane warning:	A warning that sustained winds 64 kt, 74 mph, or 119 km/hr or higher associated with a hurricane are expected in a specified coastal area in 24 hours 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: National Hurricane Center of the U.S. National Weather Service

As shown in Figure 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 warnings 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 warnings. 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. But is not obvious which is the more severe warning out of a tropical storm warning and a hurricane watch. A tropical storm warning has the

Figure 1: Storm advisory severity matrix



storm probability storm type	**Watch**	**Warning**
Tropical storm	sustained winds of 39 to 73 mph possible within 36 hours	sustained winds of 39 to 73 mph expected within 24 hours
Hurricane	sustained winds of more than 73 mph possible within 36 hours	sustained winds of more than 73 mph expected within 24 hours

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.

Table 2 gives the frequency of the storm advisory type of consecutive subsequent advisory upgrades or downgrades. These frequencies are given for each initial advisory type and give an indication of how the storm advisories increase or decrease in severity.

Storm advisories that consecutively follow tropical storm watches (column 1) are predominantly upgrades to tropical storm warnings, and tropical storm warnings usually either start a consecutive string of warnings. The pattern that emerges most clearly is that tropical storm watches and hurricane watches are usually followed by tropical storm warnings and hurricane warnings, respectively. This suggests a storm-severity ordering. However, tropical storm warnings are usually upgraded to a hurricane warning, and hurricane warnings are usually downgraded to a tropical storm warning. This pattern suggests a storm-hit-probability ordering. That is, the storm advisories should be ordered from least to most severe in the following way:

Table 2: **Frequency of consecutive subsequent advisory types by initial advisory type: all 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	61	344	74	142
no previous advisory	123	142	336	20
singleton advisory	26	66	44	0

tropical storm watch, hurricane watch, tropical storm warning, hurricane warning.

In this study, we will focus on the frequency and duration of particular types of advisories as the driving force of the fertility effect. Table 3 details the frequency of the various levels of storm advisories in U.S. Atlantic and Gulf Coast counties over the period from 1995 to 2001. Tropical storm warnings were the most common type of warning, making up about 40 percent of all storm warnings. However, hurricane watches were the second most common, making up about 24 percent of the storm warnings. It is also worth noting that most of the storm warnings (77 percent) occured in the August to September period.

Table 3: **Frequency of 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: National Hurricane Center of the U.S. National Weather Service

Also of interest to this study is the duration of storm warnings. Table 4 details these durations. Obviously, the longer a warning 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 warnings, averaging 1.2

days over the sample period. Tropical storm warnings lasted an average of 0.8 days, and both hurricane watches and tropical storm watches lasted about a half day on average.

Table 4: Duration (in Days) of Storm Advisories: 1995-2001

Advisory type	**Total advisories**	**Avg. duration**	**Std. dev.**	**Min.**	**Max.**
Tropical storm watch	36	0.58	0.69	0	2
Hurricane watch	55	0.51	0.60	0	2
Tropical storm warning	90	0.82	0.65	0	3
Hurricane warning	45	1.22	0.70	0	3
Total	226	0.79	0.70	0	3

Source: National Hurricane Center of the U.S. National Weather Service

From 1995 to 2001, some level of storm advisory was given to every U.S. coastal county 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 U.S. counties, and a more detailed listing is given in Appendix A-1.

[*Put colored county map of U.S. here to show which counties we have storm data on, which counties we have birth data on, and which counties are inland.*]

2.2 Birth data

The U.S. birth data come from the National Vital Statistics System of the National Center for Health Statistics (NCHS).[3] The data we use cover births in the United States from the years 1996 to 2002, as our earliest hurricane data come from 1995 and 2002 is the most recent birth data that is currently available.

The NCHS birth data record information on individual births in the United States. The data are collected from birth certificate information through cooperation between counties, states, and the the national government through NCHS. Included in the data is 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 and an estimate of each child's gestation period length.

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

Of the 164 U.S. coastal counties that we have storm data on, we only have birth data on 84 (*See map from end of previous section*). This is because the NCHS groups together all birth data in a given state from counties with a population of less than 100,000. We aggregate births by county of mother's residence and by month.

Figure 2: Average monthly county births in Atlantic and Gulf Coast U.S. by month and year: 1996-2002

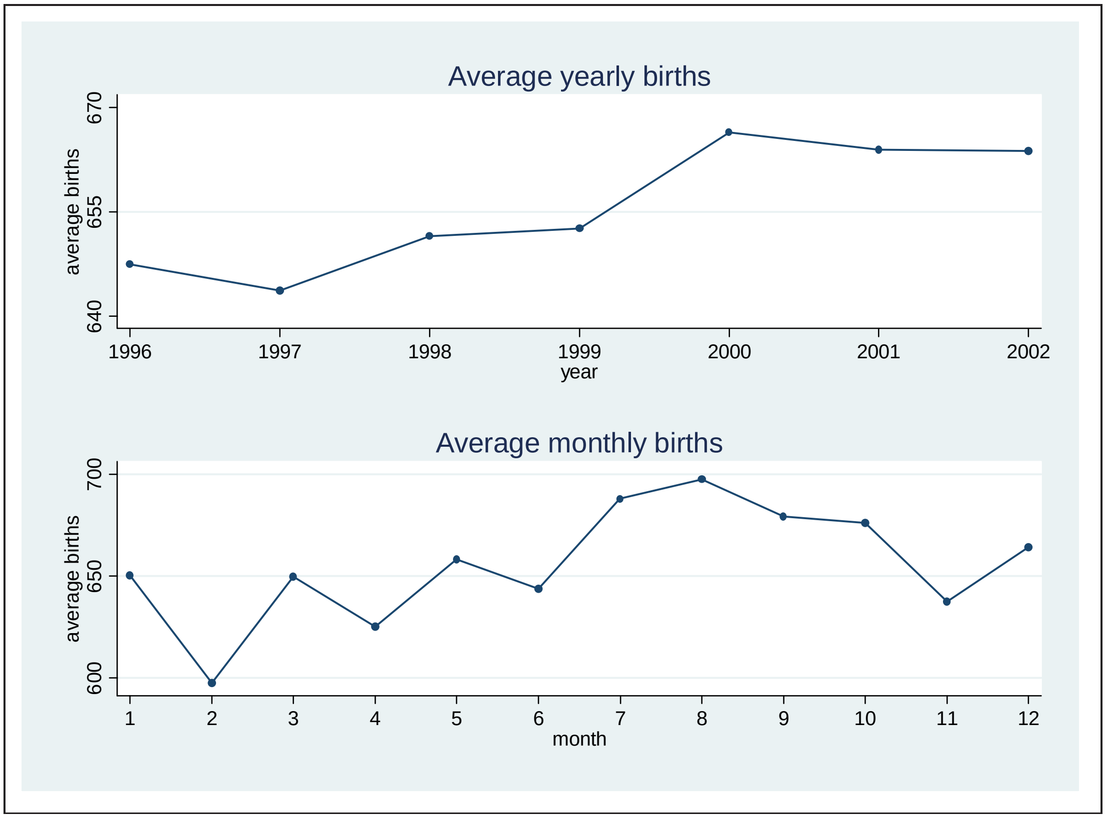

Figure 2 shows the average number of monthly births in the 84 coastal U.S. counties in our sample from 1996 to 2002, both for a given month and a given year. It is evident from the top panel that there is an upward time trend in average monthly county births across the years. The bottom panel shows the 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 in the surrounding months.

2.3 Combining hurricanes 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. But this can be done in multiple ways, so the method we choose is nontrivial.

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

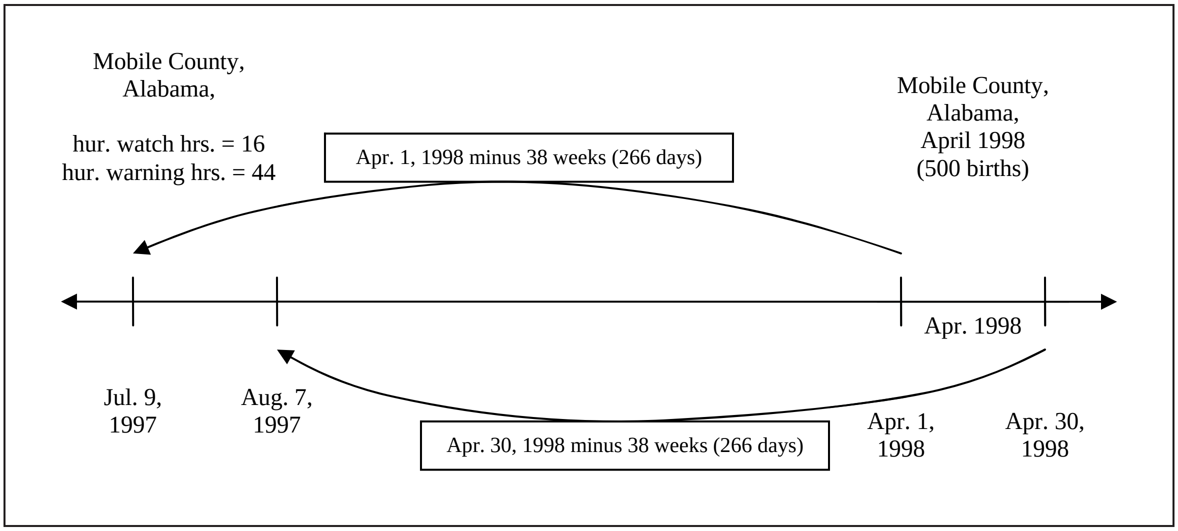

Figure 3 illustrates our strategy. From the NCHS birth data, the average gestation time for a newborn child in our sample of U.S. Atlantic and Gulf Coast counties is 38.7 weeks with a standard deviation of about 2.3 weeks—in line with the standard medical expected duration of 38 weeks. Each of our observations in the NCHS birth data is now a number of total births for a given county in a given month. We then aggregate the total minutes of each type of storm advisory for that county in the equally lengthed period 38 weeks previous as shown in Figure 3. With the hurricane data and birth data linked together in this way, we are able to measure the effect on fertility of duration of specific types of storm advisories.

To make sure the structure of our data is clear, an observation in our data is the number of births in a given county in a given month. The observation includes total minutes of each type of storm advisory in the month-long period 38 weeks previous, as well as some variables characterizing the specific county such as whether it is "slightly inland" or its population level.[4]

3 Estimation

Once the data are organized as detailed in Section 2, the estimation is simple. We use a fixed-effects model of the form in equation (1) to estimate various specifications. 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 left-hand-side of equation (1) represent the number of storm advisory type days in the period corresponding to the birth rate month (as in Figure 3) for a particular county.

$$\begin{aligned} lnbirths_{i,t} = \beta_0 + \beta_1 tswatchdays_{i,t} + \beta_2 hwatchdays_{i,t} + \beta_3 tswarndays_{i,t} + ... \\ \beta_4 hwarndays_{i,t} + \sum_{mth=Feb}^{Dec} \gamma_{mth} mth_t + \alpha t + u_{i,t} \quad (1) \end{aligned}$$

The γ terms represent a full set of eleven monthly indicator variables, which allow us to control for the seasonality in the birth data as evidenced in Table 2. We also include a time trend t to control for the increasing population growth shown in Table 2 as well. We assume that the error term $u_{i,t}$ satisfies the standard assumptions of the unobserved heterogeneity model an is normally distributed.

In order to more easily interpret our results, we have changed the unit of measure of duration of storm advisory from minutes to days. So the coefficients in our analyses represent the the effect of 24 hours of particular types of storm advisories on a specific county's number of births nine months later. Our results various specifications of equation (1) are shown in Tables 5 and 6.

Table 5 shows our baseline specification in which the storm advisory matrix $ADV_{i,t}$ includes the four types of storm advisories: tropical storm watches (*tswatchdays*), hurricane watches (*hwatchdays*), tropical storm warnings (*tswarndays*), and hurricane

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[4] Although the county population variable from the NCHS birth data had a small number of categories, we also ran our estimation analyses using a linearly interpolated county population measure taken from U.S. Census Bureau data. The choice of population measure did not end up having a significant effect on our results.

warnings (*hwarndays*). We test the robustness of this model by estimating it using both fixed-effects and random-effects econometric models. It is clear from Table 5 that the results are robust to the estimation method.

Table 5: Effect of storm advisory days on the log of monthly county births nine months later using various panel data models: 1995 to 2002

Ind. variable[a] **(in days)**	**Econometric method**	
	Fixed effects	**Random effects**
tswatch	0.020**	0.020**
	(0.009)	(0.009)
hwatch	0.004	0.004
	(0.007)	(0.007)
tswarn	-0.012**	-0.012**
	(0.004)	(0.004)
hwarn	-0.011**	-0.011**
	(0.005)	(0.005)
$F(\mathrm{df}_1, \mathrm{df}_2)$	158.65	
$\chi^2(\mathrm{df})$		2,987.11
Number of counties (I)	84	84
Number of months (T)	84	84

[a] Each specification also includes monthly indicator variables and a time trend. The random-effects model also includes the "slightly inland" variable as well as the county population measure.

[*] Significant at the 10-percent level.

[**] Significant at the 5-percent level.

In Table 6, we make the fixed-effects model our baseline estimation method and test the robustness of the results between the fixed-effects and random-effects specifications of the storm advisory measures. In doing this, the indicator for whether a county was "slightly inland" cannot be used because it does not change over time. The NCHS county population variable is also not used for the same reason. It did not change over time for any of the counties in our sample because the population measure was too course. The results are also robust to using the a linearly interpolated county population measure.

Specification 1 in Table 6 is our baseline specification. In it, we estimate the effect of each type of storm advisory separately. The key result here is that the lower-severity warnings are associated with a positive and significant effect on births in

Table 6: Fixed-effect estimates of storm advisory days on the log of monthly county births nine months later: 1995 to 2002

Ind. variable[a] (in days)	Specification 1	2	3	4	5
tswatch	0.020** (0.009)		0.017* (0.009)		
hwatch	0.004 (0.007)				
tswarn	-0.012** (0.005)				
hwatch + tswarn			-0.007** (0.003)		
hwarn	-0.011** (0.005)		-0.009* (0.005)		
tswatch + hwatch		0.010* (0.006)			
tswarn + hwarn		-0.012** (0.003)			
tswatch + tswarn				-0.003 (0.003)	
hwatch + hwarn				-0.006* (0.003)	
tswatch + tswarn + hwatch + hwarn					-0.005** (0.002)
$F(\mathrm{df}_1, \mathrm{df}_2)$	158.65	181.16	168.98	180.48	194.36
Number of counties (I)	84	84	84	84	84
Number of months (T)	84	84	84	84	84

[a] Each specification also includes monthly indicator variables and a time trend.
[*] Significant at the 10-percent level.
[**] Significant at the 5-percent level.

a given county nine months later and that an opposite effect is observed for higher-severity storm advisories. As can be seen, this result is robust across all specifications. Interpreting the results from specification 1, an extra 24 hours of tropical storm watches will increase births nine months later by 2 percent. The effect of a hurricane watch is smaller, but still positive and significant. But the effects of the higher-severity tropical storm and hurricane warnings are negative and roughly equal.

This result is beautiful given the discussion in Section 2.1 about how the different types of advisories increase in severity. In all the specifications, a smooth and nearly monotone decrease is observed in the fertility effect as severity increases. These confounding effects at either end of the severity spectrum may explain why previous studies have not been able to find a significant fertility effect of catastrophes. Specification 5 provides some evidence for this explanation of the previous literature. When all the severity levels are grouped together, the fertility effect of an extra 24 hours of any type of advisory is only associated with a 0.5-percent decrease in the birth rate of a given county nine months later. Specifications 2 through 5 are simply alternative aggregations of the four types of storm advisories.

The important finding to take away from the estimations in Table 6 is that a positive fertility effect is observed in counties that have experienced storm advisories on the lower level of the severity spectrum. But an offsetting negative fertility effect results when the storm advisories are higher severity.

4 Conclusion

The consensus in the sociological literature still seems to be that there is no positive fertility effect of catastrophes. However, using rich panel data with a large sample of multiple-severity shocks, we are able to accurately measure a positive fertility effect resulting from low level storm advisories. We also find that the sign of this fertility effect monotonically decreases and changes sign as the severity of the advisories increases.

APPENDIX

A-1 Storm Warning Data Description

Our storm-warning data come from the National Hurricane Center (NHC) of the United States National Weather Service. 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 is usually up to date up to one-month previous to the current date.

Included in the summary of each named storm is a table entitled some variant of "watch and warning summary." 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 was is often described in terms of cities or geographic features rather than affected counties. So an important step in gathering this data was carefully going through each storm advisory description in the watch and warning summary tables and mapping them into affected county terms. In 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 (MSA) that is often the recipient of the storm advisories studied in this paper.

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