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ABSTRACT

The Fertility Effect of Catastrophe: U.S. Hurricane Births*

For years, 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 United States. 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 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 at most that the highest severity storm advisories have a permanent negative fertility effect.

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 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. However, until recently, the results of studies trying to measure these effects have been mixed.[1] Our aim in this study is to quantify the fertility effect of catastrophes using U.S. storm advisory data from 1995 to 2001 and U.S. birth data from 1996 to 2002.[2]

In our study, we choose to try to measure the fertility effect of catastrophe using storm advisory data.[3] U.S. 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 U.S. county birth data, we are able to more accurately 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 U.S. 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 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.

[1] Udry (1970) finds no effect from 1965 New York City blackout but Rodgers, St. John, and Coleman (2005) find positive effect after Oklahoma City bombing.

[2] Studying different effects of hurricane impacts has attracted some attention in economics recently. Belasen and Polachek (2007) study the impact of hurricanes on local labor markets in Florida. Pörtner (2006) examines the interaction between hurricane risk and shocks, fertility, and education outcomes in developing countries. And Yang (2006) investigates the impact of hurricanes on international capital flows.

[3] We discuss in detail the reasons why we choose to use storm advisories instead of actual landfalls in Section 4.1.

Our main findings are that low-severity storm advisories are associated 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 slight 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, and Section 6 concludes.

2 Literature

The seminal empirical paper in this literature is 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 hours 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 number of births data from the New York City Health Department for the years 1961 to 1966, Udry (1970) assumed that 90 percent of babies conceived on the date of the blackout would be born within a roughly three-week range centered 266 days (38 weeks) from the date of the blackout. Calculating the mean births for each day in the same three-week period in the previous five years, Udry found that the increase in New York City births nine months after the blackout were 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 (five observations), he concluded that there was no positive fertility effect resulting from the blackout.

A more recent study by Rodgers, St. John, and Coleman (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 nine months after the bombing.[4]

The primary weakness of the studies by Udry (1970) and Rodgers, St. John, and Coleman (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 shock compared with the storm advisories studied here. For example, Belasen and Polachek (2007) find that the the effect of hurricane shocks on growth rates of earnings are temporary, and the effects last roughly two years. It is interesting that they find a hurricane stricken region experiences a positive earnings growth, while its nearby unafflicted 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 unaffect regions, and this outflow of people will create a positive labor supply shock for the nearby unafflicted regions.

Among the studies by economists, Pörtner (2006) is the closest one 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 and shocks. He

[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), Cain (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.

concludes that while hurricane risk leads to an increase in fertility, actual hurricane shocks result in a decrease in fertility. But his sample is developing countries instead of developed economies 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 Hotz and Miller (1985), Moffitt (1984a), and Rosenzweig and Schultz (1985), characterize the 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]

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. And one might expect individuals to behave differently according to the severity of a advisory. During a low-level advisory, people might spend more time at home, leading to more sexual activity because the opportunity cost of time is lower. During a high-level advisory, the opportunity cost of time 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), or 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 TV and radio for warnings and to

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

[6]The most relevant theoretical predictions to our paper are those from life-cycle models which 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).

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 is contraceptive choice during an advisory. When the people decide to engage in sexual relationships, 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 hurricane. 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 will 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 hurricane due to the probably 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 hurricane, and they need more time to save enough to finance the increased costs of rearing a child. Both effects will lead to parents postpone childbearing, and a high-level advisory will exhibit a negative impact on short-term fertility.[8] It is worth pointing out that if the hurricane stricken region experiences a rising earnings growth rate after the storm as in Belasen and Polachek (2007), 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

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

[8]See Hotz, Klerman, and Willis (1997). 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.

[9]See Heckman and Willis (1975) and Wolpin (1984).

children or the parents' life-cycle earnings profiles. If the earnings shock and relative price change resulting from a storm advisory are temporal, the fertility effect will only shift the timing of births but will not change lifetime fertility.[10]

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 in order 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 covers 164 U.S. Atlantic Coast and Gulf Coast counties. Of the 164 coastal counties for which we have storm data, only 84 have birth data as well. And only 47 of the 84 counties that have both storm and birth data have population data as well. So 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 United States National Weather Service (NWS).[11] Included is information on the name of each storm, its duration, as well as 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 is 2002. The storm advisory data and their collection are detailed more explicitly in Appendix A-1. As very few Pacific storms ever reach the western coast of the United States, we focus on storms in the Atlantic and Gulf Coasts of the United States. Our storm advisory data cover 164 Atlantic and Gulf Coast counties. Our first decision regarding how to

[10] See Hotz, Klerman, and Willis (1997).

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

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.

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 hurricane projections and advisories.[12] Because of the ability of the U.S. National Weather Service 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 still will 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 is that 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 us to make some *ad hoc* 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. But 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

[12] Conceptually, 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 and upon which they base their decisions, whereas the revised data is only available after the fact. A good reference in this literature is Orphanides (2001).

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.

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 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. But, during that time, the specific types of storm advisory may change. For example, if a county spent one hour under a hurricane watch which was then immediately upgraded to a hurricane warning that lasted for two hours, the county would have been under three hours 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. But in cases when the tropical storm warning is modified, it is almost always upgraded 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 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 U.S. 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 U.S. counties. These counties are listed and shown in Figure 2.

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 U.S. Atlantic and Gulf Coast 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 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) 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.[13] 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

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

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.

4.2 Birth data

The U.S. birth data come from the National Vital Statistics System of the National Center for Health Statistics (NCHS).[14] 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 because 2002 was the most recent birth data year available.

The NCHS birth data record information on individual births in the United States. The data are collected by NCHS from birth certificate information through cooperation among counties, states, and the the national government. 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, 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.

Figure 3 shows the counties for which we have NCHS birth data from the 19 Atlantic and Gulf Coast States. Of the 1,180 counties in the 19 coastal states, we have birth data on 236 counties. 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 U.S. coastal counties on which we have storm data (see Figure 2), the birth sample and storm advisory sample only overlap in 84 counties. However, as we will 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 4 shows the average number of monthly births in the 47 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 yearly

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

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 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. But 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 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 Figure 5, 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 duration of specific types of storm advisories on fertility.[15]

4.4 County population characteristics

The NCHS birth data described in section 4.2 have information on children actually born in the United States and on their parents. But in order to estimate the effect of storm advisories on fertility behavior, we must also control for the county level 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. Table 5 shows the distribution of county populations for our 47 counties over our 7 year period. Nearly 40 percent of our counties in a given month have populations of between 100,000 and 250,000.[16] However, just over 40 percent of the counties in a given month have populations between 250,000 and 1 million. And nearly 20 percent of our counties in a given month have populations of 1 million or above. Second, we must observe the entire population—both those who change their fertility behavior and those who do not. We use the Current Population 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. Figure 6 shows the counties represented in our final sample—counties for which we have storm advisory data, birth data, and population data. 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. However, our estimation results in section 5 do not change if we

[15] People might migrate after a hurricane hit. This will affect the birth count if the mother has the child at another place after the hurricane hit. 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 migrate.

[16] Remember that, 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.

leave out the CPS population controls in order to increase our sample size of counties.

Table 6 shows the descriptive statistics of the CPS county population variables from the 47 counties represented in our final sample from Figure 6. For most of the male and female statistics, we used age ranges representing years of generally accepted positive fertility—men age 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.

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 nine months after the advisory. 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 the ones not.

5.1 Fertility effect

To estimate the fertility effect of storm advisories, we use a random-effects model of the form in equation (1).[17] 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 equation (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 Figure 5) 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

[17] We conducted Hausman specification tests on all our specifications of this model to determine the appropriateness of using random-effects models over fixed-effect models. In all the tests, we could not reject the null hypothesis that the estimates from the two specifications were equivalent (p-values greater than 0.99), so we use a random-effects econometric model. The estimated coefficients in the two models were equivalent to the third decimal point in most specifications.

Table 5.[18]

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

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 the lower pane of Figure 4. We also include a time trend t to control for the increasing population growth shown in the upper pane of Figure 4 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. So the storm-advisory coefficients in our analysis represent the the effect of an extra 24 hours of particular types of advisories on the percentage change in a specific county's number of births nine months later. Our results for various specifications of equation (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.

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.

The first result that stands out in Table 8 is that the estimated fertility effect

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

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 hours of tropical storm watches results in an average increase in births nine months later of just over 2.1 percent, and an extra 24 hours of hurricane warnings results in an average decrease in births of 2.2 percent. Given that the average number of monthly births in our sample of coastal counties is 746, these affects mean an increase or decrease of about 16 births nine 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 low severity and high severity warnings are all significant.[19] 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 estimated positive fertility effect of tropical storm watches adds support to 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, St. John, and Coleman (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

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

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 have any children have a more inelastic demand for 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 is 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. However, if the storm advisory prompts individuals to increase their total number of children over their lifetime, then the fertility effect is permanent.

We 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 equation (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 10 shows the estimated coefficients on the four storm-advisory-types on births for three years, four years, and five years starting nine months after the storm advisory.[20]

[20]However, we must admit that this approach has a caveat and will likely result in an upward biased estimate. For example, on June 9, 1999, we have an advisory, and on August 12, 2001, we

In the three-year specification, hurricane watches and hurricane warnings have a nearly equal and opposite long-run fertility effect that is significant at the 10-percent level—hurricane watches increase a county's births by just under one percent over the following three-year period and hurricane warnings decrease the county births by about the same percentage. The pattern is similar over the four year horizon, but expectedly dissipates over the five-year horizon.[21] In Table 11 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 10.

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 (2006), and Rodgers, St. John, and Coleman (2005), all of whom find a significant long-term fertility effect. Compared to a terrorists attack or famine and war, except some extreme cases, a high-severity storm may be less likely to have profound impacts on people physically and mentally and is less 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, in developed countries such as the United States, fertility is unlikely to be used as an insurance mechanism to smooth the risk.

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 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

have another advisory, our estimates based on the birth counts in a three-year interval not only reflect long-term effect of advisory on June 9, 1999, but also are contaminated by a short-term effect of the advisory on August 12, 2001. Our approach cannot distinguish between these two effects. The results presented here, therefore, represent an upper bound of a long-term effect.

[21]We do not show the one- and two-year horizons because parents must wait at least nine months to have another child and often wait more than that. So the one- and two-year horizons predictably show an opposite pattern of the results from the three- and four-year specifications in Table 10.

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 12 and 13. Table 12 divides the parents into two groups—those who gave birth to a child conceived during a storm advisory and those gave birth to a child who was not conceived during an advisory. Table 13 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 there is no systematic difference between the infant's characteristics, such as gestation period, gender, birth-weight and Agpar score,[22] no matter whether an infant is conceived during an advisory or not, or conceived during different severity of advisory.[23] From the standard deviations in Tables 12 and 13, 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 12 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.

[22]The agpar score is an assessment of a newborn's adjustment to life immediately after birth. Five criteria are evaluated: heart rate, breathing rate, color, muscle tone and reflexes. The child is scored at one minute and 5 minutes after birth.

[23]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 to 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) need to take time.

6 Conclusion

Using rich panel data with a large sample of multiple-severity shocks, we find support for the anecdotal evidence from the media that storm advisories produce a positive fertility effect. However, our results give a much more detailed picture of how the fertility effect changes with storm advisory severity and even what types of couples are responsible for most of the changes in fertility.

We find that a positive and significant fertility effect is associated with the lowest level of storm advisory, tropical storm watches. But 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.

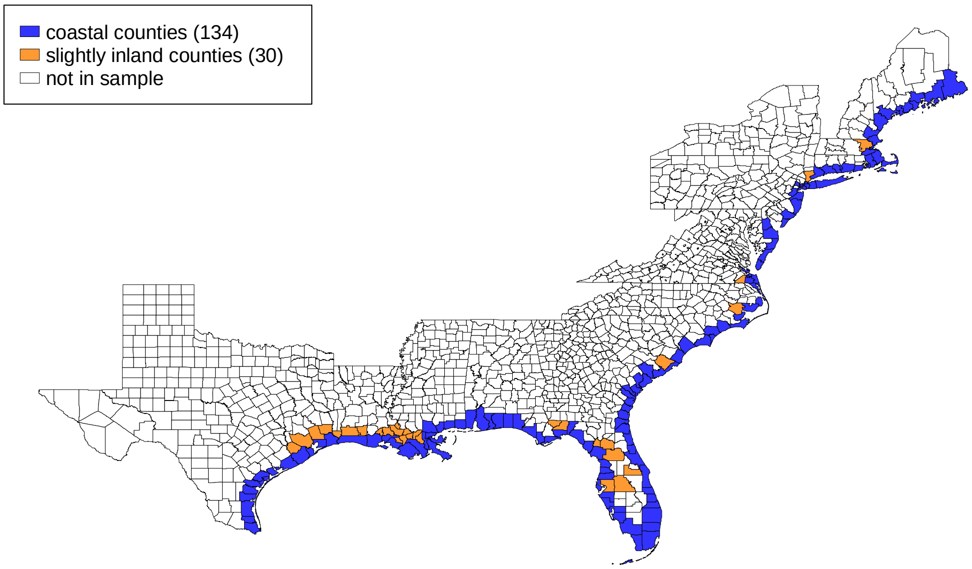
Figure 1: Storm advisory severity matrix

increasing storm probability →

increasing storm severity ↓

storm type \ storm probability	**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

Figure 2: U.S. Atlantic and Gulf Coast counties (164) in storm sample: 1995 to 2001



Atlantic and Gulf Coast U.S. counties in storm sample
(Bold counties are slightly inland from the coast)

ALABAMA
Baldwin, Mobile

CONNECTICUT
Fairfield, Middlesex, New Haven, New London

DELAWARE
Kent, Sussex

WASHINGTON D.C.
Washington D.C.

FLORIDA
Alachua, Bay, Brevard, Broward, Charlotte, Citrus, Collier, Dixie, Duval, Escambia, Flagler, Franklin, **Gadsden**, **Gilchrist**, Gulf, Hernando, **Hillsborough**, Indian River, Jefferson, Lee, **Leon**, Levy, Manatee, **Marion**, Martin, Miami-Dade, Monroe, Nassau, Okaloosa, **Orange**, Palm Beach, Pasco, Pinellas, **Polk**, St. Johns, St. Lucie, Santa Rosa, Sarasota, Taylor, Volusia, Wakulla, Walton

GEORGIA
Bryan, Camden, Chatham, Glynn, Liberty, McIntosh

LOUISIANA
Ascension, **Assumption**, **Calcasieu**, Cameron, Iberia, **Iberville**, Jefferson, **Jefferson Davis**, **Lafayette**, Lafourche, Orleans, Plaquemines, St. Bernard, **St. Charles**, **St. James**, **St. John the Baptist**, **St. Martin**, St. Mary, St. Tammany, Terrebonne, Vermilion, **West Baton Rouge**

MAINE
Cumberland, Hancock, Knox, Lincoln, Sagadahoc, Waldo, Washington, York

MARYLAND
Worcester

MASSACHUSETTS
Barnstable, Bristol, Dukes, Essex, **Middlesex**, Nantucket, Norfolk, Plymouth, Suffolk

MISSISSIPPI
Hancock, Harrison, Jackson

NEW HAMPSHIRE
Rockingham

NEW JERSEY
Atlantic, Cape May, Essex, Hudson, Middlesex, Monmouth, Ocean

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

NORTH CAROLINA
Beaufort, Brunswick, Carteret, Currituck, Dare, Hyde, New Hanover, Onslow, Pamlico, Pender

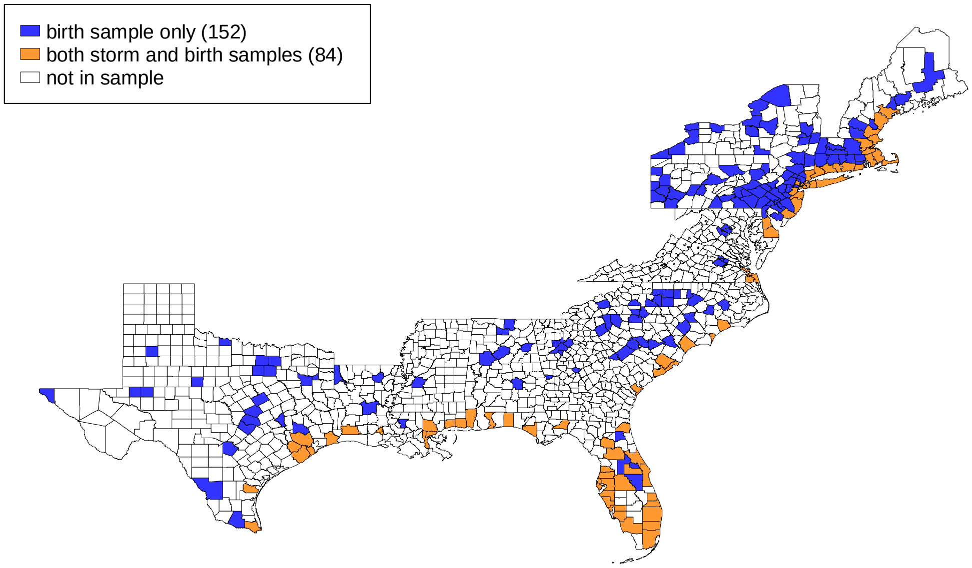
RHODE ISLAND
Newport, Washington

SOUTH CAROLINA
Beaufort, **Berkeley**, Charleston, Colleton, Georgetown, Horry, Jasper

TEXAS
Aransas, Brazoria, Calhoun, Cameron, Chambers, **Fort Bend**, Galveston, **Hardin**, **Harris**, Jefferson, Kenedy, Kleberg, **Liberty**, Matagorda, Nueces, **Orange**, Refugio, San Patricio, Willacy

VIRGINIA
Accomack, Chesapeake city, Hampton city, Newport News city, Norfolk city, Northampton, Poquoson city, Portsmouth City, **Suffolk city**, Virginia Beach city

Figure 3: U.S. Atlantic and Gulf Coast counties (236) in birth data sample: 1996 to 2002



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

ALABAMA

Calhoun
Jefferson
Madison
Mobile
Montgomery
Morgan
Tuscaloosa

CONNECTICUT

Fairfield
Hartford
Litchfield
Middlesex
New Haven
New London
Tolland
Windham

DELAWARE

Kent
New Castle
Sussex

WASHINGTON D.C.

Washington D.C.

FLORIDA

Alachua
Bay
Brevard
Broward
Charlotte
Clay
Collier
Miami-Dade
Duval
Escambia
Hernando
Hillsborough
Lake
Lee
Leon
Manatee
Marion
Martin
Okaloosa
Orange
Osceola
Palm Beach
Pasco
Pinellas
Polk
St. Lucie
Sarasota
Seminole
Volusia

GEORGIA

Bibb
Chatham
Clayton
Cobb
De Kalb
Fulton
Gwinnett
Muscogee
Richmond

LOUISIANA

Caddo
Calcasieu
East Baton Rouge
Jefferson
Lafayette
Orleans
Ouachita
Rapides
St. Tammany

MAINE

Androscoggin
Cumberland
Kennebec
Penobscot
York

MASSACHUSETTS

Barnstable
Berkshire
Bristol
Essex
Hampden
Hampshire
Middlesex
Norfolk
Plymouth
Suffolk
Worcester

MISSISSIPPI

Harrison
Hinds
Jackson

NEW HAMPSHIRE

Hillsborough
Merrimack
Rockingham
Strafford

NEW JERSEY

Atlantic
Bergen
Burlington
Camden
Cumberland
Essex
Gloucester
Hudson
Hunterdon
Mercer
Middlesex
Monmouth
Morris
Ocean
Passaic
Somerset
Sussex
Union

NEW YORK

Albany
Bronx
Broome
Chautauqua
Dutchess
Erie
Jefferson
Kings
Monroe
Nassau
New York
Niagara
Oneida
Onondaga
Orange
Oswego
Queens
Rensselaer
Richmond
Rockland
St. Lawrence
Saratoga
Schenectady
Suffolk
Ulster
Westchester

NORTH CAROLINA

Alamance
Buncombe
Catawba
Cumberland
Davidson
Durham
Forsyth
Gaston
Guilford
Mecklenburg
New Hanover
Onslow
Pitt
Randolph
Robeson
Rowan
Wake
Wayne

PENNSYLVANIA

Allegheny
Beaver
Berks
Blair
Bucks
Butler
Cambria
Centre
Chester
Cumberland
Dauphin
Delaware
Erie
Fayette
Franklin
Lackawanna
Lancaster
Lebanon
Lehigh
Luzerne
Lycoming
Mercer
Montgomery
Northampton
Philadelphia
Schuylkill
Washington
Westmoreland
York

RHODE ISLAND

Kent
Providence
Washington

SOUTH CAROLINA

Aiken
Anderson
Berkeley
Charleston
Florence
Greenville
Horry
Lexington
Richland
Spartanburg
Sumter
York

TEXAS

Bell
Bexar
Brazoria
Brazos
Cameron
Collin
Dallas
Denton
Ector
El Paso
Fort Bend
Galveston
Gregg
Harris
Hidalgo
Jefferson
Lubbock
McLennan
Midland
Montgomery
Nueces
Smith
Tarrant
Taylor
Travis
Webb
Wichita
Williamson

VIRGINIA

Arlington
Chesterfield
Fairfax
Henrico
Prince William
Alexandria City
Chesapeake City
Hampton City
Newport News City
Norfolk City
Portsmouth City
Richmond City
Virginia Beach City

Figure 4: Average monthly county births in Atlantic and Gulf Coast U.S. by month and year: 47 counties, 1996-2002

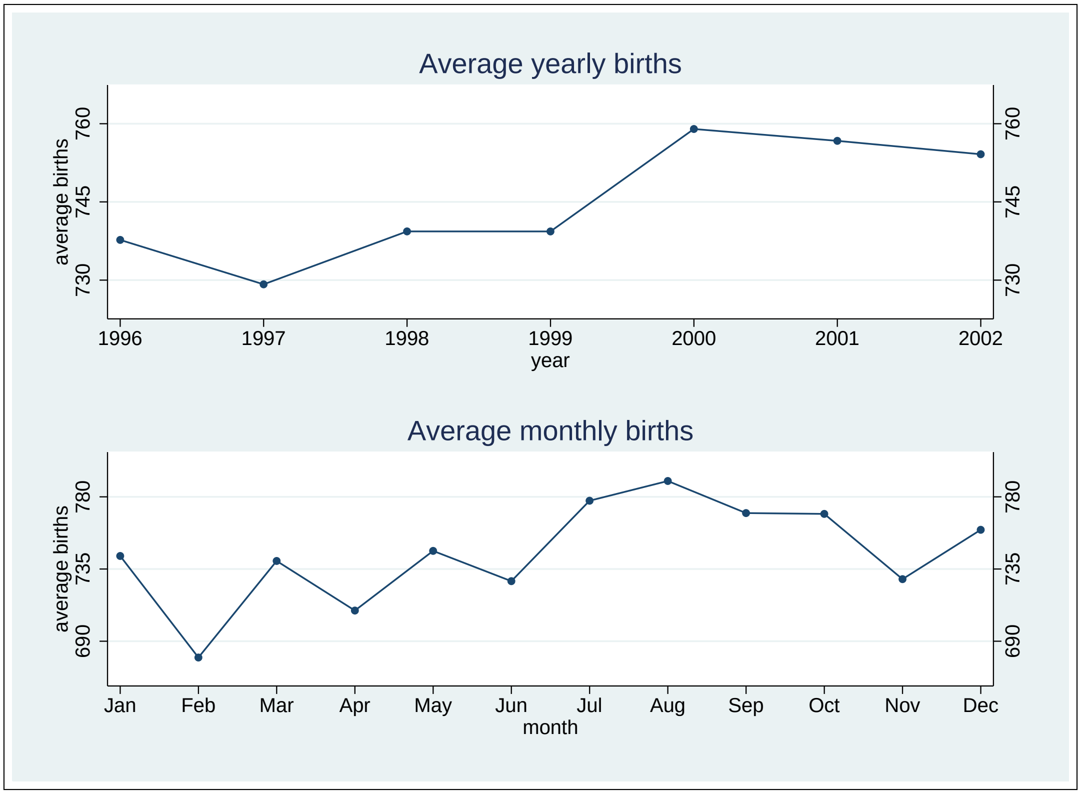


Figure 5: Correspondence between births per month and duration of storm advisories: example Mobile County, Alabama

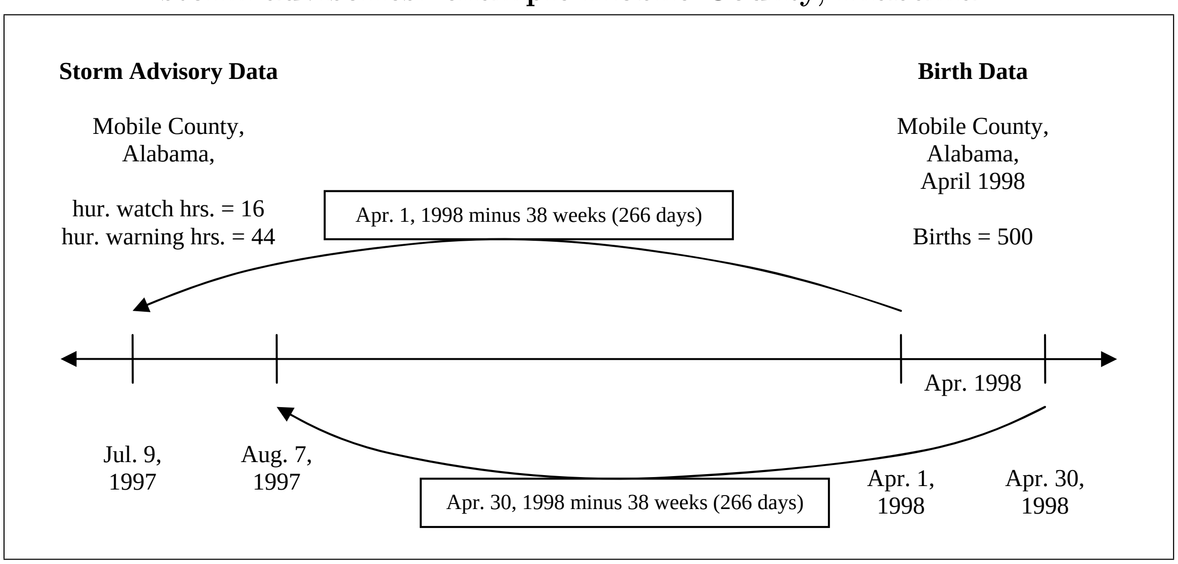
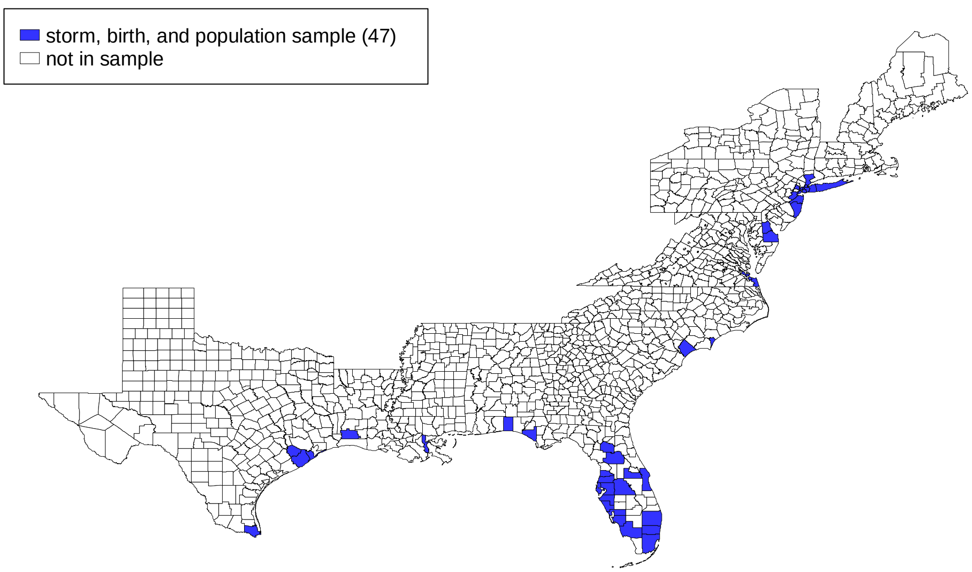


Figure 6: U.S. Atlantic and Gulf Coast counties (47) in final sample



Atlantic and Gulf Coast U.S. counties in final sample
These counties have storm, birth, and population data

DELAWARE
Kent, Sussex

WASHINGTON D.C.
Washington D.C.

FLORIDA
Alachua, Bay, Brevard, Broward, Charlotte, Collier, Miami-Dade, Hernando, Hillsborough, Lee, Manatee, Marion, Okaloosa, Orange, Palm Beach, Pasco, Pinellas, Polk, Sarasota

LOUISIANA
Calcasieu, Jefferson

NEW JERSEY
Essex, Hudson, Middlesex, Monmouth, Ocean

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

NORH CAROLINA
New Hanover

SOUTH CAROLINA
Horry

TEXAS
Brazoria, Cameron, Fort Bend, Galveston

VIRGINIA
Hampton City, Newport News City, Norfolk City, Virginia Beach City

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

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

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

Table 5: Distribution of county population: 47 counties, 75 months, 1995-2001

Population Category	Frequency	Percent
100,000 to 250,000	1,350	38.3
250,000 to 500,000	750	21.3
500,000 to 1 million	750	21.3
1 million and above	675	19.1
Total	3,525	100.0

Source: Authors' own calculation from the NCHS birth data.

Table 6: Summary statistics of CPS monthly county-specific population data: 1995 to 2001 (47 counties, 75 months, 3,525 county months)

County-month variables	Mean[a]	Std. Dev.
Total monthly births[b]	746.7	738.0
Avg. age of all males	36.2	5.4
Avg. age of all females	38.8	5.3
Avg. years of education for males (age 16 and up)	13.1	0.8
Avg. years of education for females (age 16 to 40)	13.1	0.8
Percent of women married (age 16 to 40)	0.445	0.141
Unemployment rate	0.051	0.037
Avg. number of children per household	0.60	0.220
Percent white males (age 16 and up)	0.820	0.160
Percent white females (age 16 to 40)	0.761	0.179
Avg. household income	44,605	13,799

[a] 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.
[b] The total births variable comes from the NHVS birth data, not from the CPS, and corresponds to Figure 4.

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*	0.021*
	(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**	-0.022**
	(0.008)	(0.008)
$F(\text{df}_1, \text{df}_2)$	62.84	
$\chi^2(\text{df})$		1,907.91
Observations	3,525	3,525
Counties (I)	47	47
Months (T)	75	75
Hausman $\chi^2(\text{df})$	1.01	

[a] Each specification also includes monthly indicator variables, a time trend, and population characteristics from the CPS as detailed in section 4.4.
[*] Significant at the 10-percent level.
[**] Significant at the 5-percent level.

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

Ind. variables[a] (duration in days)	Specification 1	2	3	4	5
Tropical storm watch	0.021*		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**		-0.020**		
	(0.008)		(0.008)		
Trop. storm watch + hur. watch		0.013*			
		(0.007)			
Trop. storm warning + hur. warning		-0.009**			
		(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.
[*] Significant at the 10-percent level.
[**] Significant at the 5-percent level.

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

Ind. variables[a] **(duration in days)**	**Sample**	
	Firstborn	**Non-firstborn**
Tropical storm watch	0.015	0.025*
	(0.016)	(0.015)
Hurricane watch	-0.001	0.018*
	(0.012)	(0.011)
Tropical storm warning	-0.005	-0.001
	(0.008)	(0.007)
Hurricane warning	-0.011	-0.028**
	(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.
* Significant at the 10-percent level.
** Significant at the 5-percent level.

Table 10: Random-effects estimates of storm advisory days on the log of long duration county births beginning nine 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**
	(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*	-0.007**
	(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.
* Significant at the 10-percent level.
** Significant at the 5-percent level.

Table 11: Random-effects estimates of storm advisory days on the log of long duration county births for firstborn and non-firstborn children beginning nine months later: 1995 to 2002

Ind. variables[a] **(duration in days)**	**Log of long-term total births:** **Firstborn** 5 yrs.	4 yrs.	3 yrs.	**Non-firstborn** 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**	-0.002	0.005	0.008**
	(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**	-0.008**	-0.000	-0.006	-0.006*
	(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.
[*] Significant at the 10-percent level.
[**] Significant at the 5-percent level.

Table 12: 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	38.74	38.71	38.74
	in weeks	(2.68)	(2.73)	(2.67)
	percent male	0.5121	0.5116	0.5121
		(0.4999)	(0.4999)	(0.4999)
	birthweight	3,280.4	3,285.7	3,280.0
	in grams	(610.5)	(615.5)	(610.1)
	children per birth	1.035	1.034	1.035
	(twins, etc.)	(0.197)	(0.195)	(0.197)
	Apgar score	8.964	8.947	8.965
	(range: 1 - 10)	(0.711)	(0.731)	(0.710)
	percent	0.420	0.414	0.420
	firstborn	(0.494)	(0.492)	(0.494)
Mothers:	mother's age	27.96	27.74	27.97
	in years	(6.30)	(6.26)	(6.30)
	hispanic mothers	0.261	0.232	0.263
		(0.439)	(0.422)	(0.440)
	white mothers	0.684	0.707	0.683
		(0.465)	(0.455)	(0.465)
	mother's education	12.88	12.91	12.87
	in years	(2.81)	(2.73)	(2.82)
	married mothers	0.624	0.634	0.623
		(0.485)	(0.482)	(0.485)
Fathers:	father's age	31.46	31.26	31.48
	in years	(7.01)	(6.97)	(7.01)
	hispanic fathers	0.242	0.209	0.244
		(0.428)	(0.406)	(0.429)
	white fathers	0.725	0.749	0.723
		(0.447)	(0.434)	(0.447)

Table 13: 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: Tropical storm watch	Hurricane watch	Tropical 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)

APPENDIX

A-1 Storm Advisory Data Description

Our storm advisory 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. In the broad sample of 164 counties for which we had storm advisory data, 30 counties were characterized as being "slightly inland". Figure 2 shows the counties in the hurricane sample and highlights those designated as slightly inland. Of the subsample of 84 counties for which we had both birth data and storm advisory data, only 14 were "slightly inland".

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