Analyses on Hurricane Archival Data

June 17, 2014

This report provides detailed information about analyses of archival data in our PNAS article http://www.pnas.org/content/early/2014/05/29/1402786111.abstract and addresses a number of comments. References are listed at the end. Here, we provided the syntax as well as raw results from STATA. In cases where we found minor errors or data that needed to be updated, we have done that. Note that these analyses apply the robust or sandwich estimator, vce(robust), to adjust extra SEs (extra correlations). This is suggested to be the default standard error for count models by Cameron & Trivedi (2013), Hilbe (2011, 2014), and Winkelmann (2008). A few statistics are affected to some extent as a result of this adjustment, but not the conclusions. Note that we focus on the final model specification reported in the article (Model 4 in Table S2) because it is based on the theorizing presented in the article.

Comment #1: Hurricane Sandy seems like it should have been classified as a gender-neutral name. Was assigning a highly feminine masculine-feminine index (MFI) score to Hurricane Sandy necessary to observing the results?

To address this, we ran the analysis as in the original paper. We then dropped hurricane Sandy and re-ran the analysis. The primary finding from the comparison is that dropping Sandy does not significantly change the parameters. In addition, changing MFI values of Sandy only leads to minor changes. In fact, the model is strengthened after dropping Sandy.

First, two interaction terms are generated as specified below:

```
. gen mxm = ZMasFem* ZMinPressure_A

. gen mxn = ZMasFem* ZNDAM
```

We tested a negative binomial regression model (Model 4). The syntax code and the results are shown below:

```
. glm alldeaths ZMasFem ZMinPressure_A ZNDAM mxm mxn, fam(nb ml) vce(robust)
nolog

Generalized linear models                      No. of obs      =       92
Optimization     : ML                         Residual df     =       86
                                              Scale parameter =        1
Deviance         =  102.8265238                (1/df) Deviance =  1.195657
Pearson          =  94.12118823                (1/df) Pearson  =  1.094432

Variance function: V(u) = u+(1.2327)u^2          [Neg. Binomial]
```

```
Link function    : g(u) = ln(u)                    [Log]
                                                   AIC             =   7.13142
Log pseudolikelihood = -322.0453217                BIC             = -286.0473

------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ZMasFem |   .1723216   .1187032     1.45   0.147    -.0603323    .4049755
ZMinPressure_A |  -.5520594    .147599    -3.74   0.000    -.8413481   -.2627707
       ZNDAM |   .8634609   .3332535     2.59   0.010      .210296    1.516626
         mxm |   .3947513   .1565007     2.52   0.012     .0880156     .701487
         mxn |   .7050947   .2468475     2.86   0.004     .2212826    1.188907
       _cons |   2.475622   .1254586    19.73   0.000     2.229728    2.721517
------------------------------------------------------------------------------
Note: Negative binomial parameter estimated via ML and treated as fixed once
estimated.

. abic
AIC Statistic    =    7.13142          AIC*n       = 656.09064
BIC Statistic    =   7.234693          BIC(Stata)  = 671.22137
```

This replicated the finding. There are small differences due to adjusting extra SEs with a robust estimator. To fully replicate, vce(robust) can be removed from the syntax.

We now drop Sandy and re-run the analysis.

```
. drop if NDAM == 75000
(1 observation deleted)

. glm alldeaths ZMasFem ZMinPressure_A ZNDAM mxm mxn, fam(nb ml) vce(robust)
nolog

Generalized linear models                          No. of obs      =        91
Optimization     : ML                              Residual df     =        85
```

```
                                              Scale parameter =        1
Deviance         =  101.2916751                  (1/df) Deviance =  1.191667
Pearson          =   87.5597205                  (1/df) Pearson  =  1.030114

Variance function: V(u) = u+(1.1408)u^2           [Neg. Binomial]
Link function    : g(u) = ln(u)                  [Log]
                                                  AIC           =  6.987262
Log pseudolikelihood = -311.9204154               BIC           = -282.1314

------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ZMasFem |   .1833017   .1165205     1.57   0.116    -.0450742    .4116777
ZMinPressure_A |  -.5375679    .142838    -3.76   0.000    -.8175254   -.2576105
       ZNDAM |   1.085118   .2879344     3.77   0.000      .520777    1.649459
         mxm |   .3892216   .1493563     2.61   0.009     .0964886    .6819545
         mxn |   .8486833   .2203004     3.85   0.000     .4169025    1.280464
       _cons |   2.496933   .1250726    19.96   0.000     2.251796    2.742071
------------------------------------------------------------------------------
Note: Negative binomial parameter estimated via ML and treated as fixed once
estimated.

. abic
AIC Statistic   =    6.987262          AIC*n      = 635.84082
BIC Statistic   =     7.09167          BIC(Stata) = 650.90601
```

Below is the comparison of key statistics with and without Hurricane Sandy.

With Sandy:

```
(1/df) Pearson  =  1.094432
------------------------------------------------------------------------------
```

```
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         mxn |   .7050947   .2468475     2.86   0.004     .2212826    1.188907
       _cons |   2.475622   .1254586    19.73   0.000     2.229728    2.721517
------------------------------------------------------------------------------
AIC Statistic  =    7.13142           AIC*n      = 656.09064
BIC Statistic  =   7.234693           BIC(Stata) = 671.22137
```

Without Sandy:

```
(1/df) Pearson  =  1.030114
------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         mxn |   .8486833   .2203004     3.85   0.000     .4169025    1.280464
       _cons |   2.496933   .1250726    19.96   0.000     2.251796    2.742071
------------------------------------------------------------------------------
AIC Statistic  =   6.987262           AIC*n      = 635.84082
BIC Statistic  =    7.09167           BIC(Stata) = 650.90601
```

The dispersion statistic (1/df Pearson), fit statistic (AIC*n and BIC) and the interaction effect (mxn) all provide stronger evidence for our main hypothesis. If the gender effect needed to be inflated for some reason, it could have been achieved by dropping Sandy as an outlier.

Comment #2: Year effects should be included in the model as there have been numerous changes over time affecting hurricane fatalities (improved warning technology, building codes, institutional resources, etc.).

This was addressed in the article. Here we show the negative binomial regression model with elapsed years. The model without the year variable is already provided under #1 above.

```
. glm alldeaths ZMasFem ZMinPressure_A ZNDAM mxm mxn ElapsedYrs, fam(nb ml)
vce(robust) nolog

Generalized linear models                          No. of obs      =        92
```

```
Optimization     : ML                            Residual df     =        85
                                                Scale parameter =         1
Deviance         =  102.8176984                     (1/df) Deviance =   1.20962
Pearson          =  94.15039728                     (1/df)  Pearson  =  1.107652
Variance function: V(u) = u+(1.2327)u^2             [Neg. Binomial]
Link function    : g(u) = ln(u)                     [Log]
                                                AIC             =  7.153115
Log pseudolikelihood = -322.0432671             BIC             = -281.5343
------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ZMasFem |   .1760512   .1316019     1.34   0.181    -.0818838    .4339861
ZMinPressure_A |  -.5502107   .1487333    -3.70   0.000    -.8417225   -.2586988
       ZNDAM |   .8667357   .3537552     2.45   0.014     .1733882    1.560083
         mxm |    .394799   .1563331     2.53   0.012     .0883918    .7012061
         mxn |   .7073273   .2569652     2.75   0.006     .2036848     1.21097
  ElapsedYrs |  -.0004708   .0082766    -0.06   0.955    -.0166928    .0157511
       _cons |   2.490213    .282062     8.83   0.000     1.937381    3.043044
------------------------------------------------------------------------------
Note: Negative binomial parameter estimated via ML and treated as fixed once
estimated.

. abic

AIC Statistic    =   7.153114          AIC*n      = 658.08655
BIC Statistic    =   7.297057          BIC(Stata) = 675.73907
```

There are no significant changes after adding the year variable into the model. We now compare the model with the year variable vs. the model without the year variable using key statistics.

A model without the year variable:

```
(1/df)  Pearson  =  1.094432
------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
----------------+----------------------------------------------------------------
            mxn |   .7050947   .2468475     2.86   0.004     .2212826    1.188907
          _cons |   2.475622   .1254586    19.73   0.000     2.229728    2.721517
---------------------------------------------------------------------------------
AIC Statistic   =    7.13142          AIC*n      = 656.09064
BIC Statistic   =   7.234693          BIC(Stata) = 671.22137
```

A model with the year variable:

```
(1/df) Pearson  =  1.107652
---------------------------------------------------------------------------------
                |               Robust
      alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
            mxn |   .7073273   .2569652     2.75   0.006     .2036848     1.21097
     ElapsedYrs |  -.0004708   .0082766    -0.06   0.955    -.0166928    .0157511
          _cons |   2.490213    .282062     8.83   0.000     1.937381    3.043044
. abic
AIC Statistic   =   7.153114          AIC*n      = 658.08655
BIC Statistic   =   7.297057          BIC(Stata) = 675.73907
```

The dispersion statistic shows marginal improvement after adding the year variable. However, the model fit statistics get slightly worse (see BIC). The year variable does not have a significant effect, and it does not alter any conclusions. This is why we dropped the year variable in the reported models, as stated in the article.

Comment #3: What about the gender of names as a binary variable (male vs. female name)?

The article, in line with our theorizing, focused on gender of names as a continuous variable (MFI). Below we evaluate two separate negative binomial regression models: one with MFI and the other with binary gender. For the syntax and the results for the model with MFI, please refer to the results under #1. Here are the results of the model with the binary gender variable. To begin, we generated two interaction terms as specified below and tested a negative binomial regression model while considering the gender of names as a binary variable.

```
. gen mxm2 = Gender_MF* ZMinPressure_A
. gen mxn2 = Gender_MF* ZNDAM
.  glm  alldeaths  Gender_MF  ZMinPressure_A  ZNDAM  mxm2  mxn2,  fam(nb  ml)
```

```
vce(robust) nolog

Generalized linear models                         No. of obs      =        92
Optimization     : ML                             Residual df     =        86
                                                  Scale parameter =         1
Deviance         =  103.1630471                   (1/df) Deviance =   1.19957
Pearson          =   107.658489                   (1/df) Pearson  =  1.251843

Variance function: V(u) = u+(1.2693)u^2           [Neg. Binomial]
Link function    : g(u) = ln(u)                   [Log]

                                                  AIC             =  7.161829
Log pseudolikelihood = -323.4441176               BIC             = -285.7108

------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Gender_MF |   .3828388   .2572398     1.49   0.137    -.1213419    .8870196
ZMinPressure_A |  -.9881641   .2752044    -3.59   0.000    -1.527555   -.4487735
       ZNDAM |  -.0495457   .1945473    -0.25   0.799    -.4308514      .33176
        mxm2 |   .7381847     .34462     2.14   0.032     .0627419    1.413627
        mxn2 |   1.432673   .5535594     2.59   0.010      .347716    2.517629
       _cons |   2.229466   .1836495    12.14   0.000      1.86952    2.589413
------------------------------------------------------------------------------
Note: Negative binomial parameter estimated via ML and treated as fixed once
estimated.

. abic

AIC Statistic    =   7.161829          AIC*n      = 658.88824
BIC Statistic    =   7.265101          BIC(Stata) = 674.01898
```

This replicates the finding even when treating the gender of hurricane names as a binary variable.

[Note that we discovered a typo in the sign of a corresponding parameter estimation for model 3, published in the paper. For the interaction of binary gender and minimum pressure it should have read β = 0.038 (not β = - 0.038).]

Comment #4: The alternating male-female naming system was adopted in 1979. What happens if you do not use pre-1979 hurricane data?

As noted in #3, the article focused on gender of names as a continuous variable (MFI), which allows for the possibility of within-gender variability of perceived masculinity-femininity. Therefore, the entire data set was used including hurricanes before 1979. We addressed this point in a previous statement. Here, we show that the gender effect emerges when using hurricane data since 1979. Note that, in the article, we neglected to apply the robust estimator to adjust extra SEs. Here, that adjustment is made as recommended (see references). To begin, the hurricane data before 1979 are dropped.

```
. drop if Year < 1979

(38 observations deleted)
```

There are 54 observations left. We delete the standardized variables and interaction terms used in the previous analyses and standardize the key variables again.

```
. drop ZMasFem ZMinPressure_A ZNDAM mxm mxn mxm2 mxn2

. egen float zmfi = std(MasFem), mean(0) std(1)

. egen float zmpress = std(MinPressure_before), mean(0) std(1)

. egen float zndam = std(NDAM), mean(0) std(1)
```

Continuous gender variable (MFI)

We begin the analysis with the continuous gender variable (zmfi). Two interaction terms were generated as in the previous analysis:

. gen mxm = zmfi*zmpress

. gen mxn = zmfi*zndam

We tested a negative binomial regression model, which is specified identically as in the previous analyses:

```
. glm alldeaths zmfi zmpress zndam mxm mxn, fam(nb ml) vce(robust) nolog

Generalized linear models                         No. of obs      =        54

Optimization     : ML                           Residual df     =        48

                                              Scale parameter =         1

Deviance         =  58.47719154                   (1/df) Deviance =  1.218275

Pearson          =  53.91372101                   (1/df) Pearson  =  1.123203

Variance function: V(u) = u+(.8636)u^2             [Neg. Binomial]

Link function    : g(u) = ln(u)                  [Log]
```

```
                                                AIC             =  6.938826
Log pseudolikelihood = -181.3483038             BIC             =  -132.994

------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        zmfi |   .0001948   .1370233     0.00   0.999     -.268366    .2687556
     zmpress |   -.817058   .1796183    -4.55   0.000    -1.169103   -.4650126
       zndam |   .1687693   .1138009     1.48   0.138    -.0542764    .3918151
         mxm |   .2308253   .1756816     1.31   0.189    -.1135043    .5751549
         mxn |   .3283444    .114578     2.87   0.004     .1037757    .5529131
       _cons |   2.324059   .1374705    16.91   0.000     2.054622    2.593497
------------------------------------------------------------------------------
Note: Negative binomial parameter estimated via ML and treated as fixed once
estimated.

. abic

AIC Statistic  =   6.975863          AIC*n      = 376.69659
BIC Statistic  =   7.221099          BIC(Stata) = 390.61951
```

Using only hurricane data since 1979 demonstrates the gender effect. There is a significant interaction between standardized MFI and standardized normalized damage (mxn in the model). However, there is no interaction between standardized MFI and standardized minimum pressure.

Binary gender variable

Here, the gender of names is treated as a binary variable (male vs. female name). To begin, we generate two interaction terms as shown below and run the negative binomial regression analysis.

```
. gen mxm2 = Gender_MF *zmpress

. gen mxn2 = Gender_MF *zndam

. glm alldeaths Gender_MF zmpress zndam mxm2 mxn2, fam(nb ml) vce(robust)
nolog

Generalized linear models                          No. of obs      =        54
Optimization     : ML                              Residual df     =        48
                                                   Scale parameter =         1
Deviance         =  58.63644419                    (1/df) Deviance =  1.221593
```

```
Pearson         =  53.54256381                (1/df) Pearson  =   1.11547
Variance function: V(u) = u+(.8773000000000001)u^2 [Neg. Binomial]
Link function    : g(u) = ln(u)                   [Log]
                                                  AIC           =  6.955454
Log pseudolikelihood = -181.7972698               BIC           = -132.8348
------------------------------------------------------------------------------
             |               Robust
   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Gender_MF |   .0356374   .2762525     0.13   0.897    -.5058075    .5770823
     zmpress |  -.9837294    .272392    -3.61   0.000    -1.517608   -.4498509
       zndam |  -.0908992   .2160004    -0.42   0.674    -.5142522    .3324538
        mxm2 |   .3631462   .3617246     1.00   0.315    -.3458211    1.072113
        mxn2 |   .5511261   .2369163     2.33   0.020     .0867787    1.015474
       _cons |   2.302767   .1925234    11.96   0.000     1.925428    2.680106
------------------------------------------------------------------------------
Note: Negative binomial parameter estimated via ML and treated as fixed once
estimated.
. abic
AIC Statistic  =   6.955454          AIC*n       = 375.59454
BIC Statistic  =   7.131401          BIC(Stata)  = 387.52844
```

Again, the current model using the binary gender variable showed a significant interaction of the binary gender of names and standardized normalized damage (mxn2 in the model). In other words, the key gender effect emerges even when using the data since 1979 and treating gender of hurricane name as a binary variable. Note that as with the previous MFI analysis, there is no interaction between binary gender and standardized minimum pressure.

Comment #5: The interaction between MFI and minimum pressure suggests an opposite relationship between hurricane severity and hurricane name. Why not interpret this interaction?

We focus on the interaction between MFI and normalized damage rather than the interaction between MFI and minimum pressure for the following reasons. First, we are interested in human responses to hurricane information. A priori, normalized damage is more reflective of the impact of a storm on human population centers than is minimum pressure. For instance, some strong low-pressure systems do not hit highly populated areas, whereas some higher-pressure systems do.

Nonetheless, we did look at the role of minimum pressure as an indicator of severity but failed to find the interaction emerging reliably. Across the full sample of storms (N=92) there is a weak and opposite tendency, but a bootstrapping test (1200 samples – see below for details) did not show statistical significance for this interaction. Moreover, the interaction was not observed in the data since 1979 (see models in #4). Note that typically minimum pressure and normalized damage are inversely related and they are correlated at -.556 in the dataset. The significant interaction we observed for minimum pressure is caused by a few feminine-named hurricanes that are high in minimum pressure *and* high in normalized damage (e.g., Hurricane Agnes in 1972: deaths = 117, minimum pressure = 980, normalized damage = 20430; Hurricane Diane in 1955: deaths = 200, minimum pressure = 987, normalized damage = 14730). The interaction therefore suggests that, when hurricanes are less severe in terms of minimum pressure, feminine-named hurricanes are deadlier. For instance, for storms with high minimum pressure, a masculine-named hurricane (MFI = 3) is estimated to cause 5.4 deaths whereas a feminine-named hurricane (MFI = 9) is estimated to cause 10.6 deaths. When hurricanes are severe in terms of minimum pressure (low minimum pressure) masculine hurricanes are slightly deadlier. For example, a masculine-named hurricane with low minimum pressure (MFI = 3) is estimated to cause 20.2 deaths whereas a feminine-named hurricane with low minimum pressure (MFI = 9) is estimated to cause 17.8 deaths.

As noted, the interaction involving minimum pressure does not emerge reliably. We conducted a bootstrapping test (with 1200 resamples) to check the robustness of each interaction. It shows that the focal interaction between MFI and normalized damage remains significant (P = .035) but the interaction between MFI and minimum pressure is only marginally significant (P= .077). Please refer to the code and results below.

See also the models in #4 above, as well as the summary table on the next page.

Because the interaction effect involving minimum pressure is not robust and appears due to a few observations of highly damaging yet high-pressure storms, it does not seem appropriate to interpret it. The evidence across these analyses does not support a conclusion that masculine-named low pressure storms are deadlier.

```
bootstrap, reps(1200) bca: nbreg alldeaths c.ZMasFem##(c.ZMinPressure_A
```

```
c.ZNDAM), vce(robust)
(running nbreg on estimation sample)

Jackknife replications (92)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Bootstrap replications (1200)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................  1200

Negative binomial regression                     Number of obs   =         92
Dispersion          = mean                       Wald chi2(5)    =      43.29
Log pseudolikelihood = -322.04532                Prob > chi2     =     0.0000

------------------------------------------------------------------------------
                             |   Observed   Bootstrap                         Normal-based
                   alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------------+----------------------------------------------------------------
                     ZMasFem |   .1723216   .1406677     1.23   0.221    -.1033821    .4480252
              ZMinPressure_A |  -.5520594   .2005179    -2.75   0.006    -.9450672   -.1590515
                       ZNDAM |   .8634609   .3738815     2.31   0.021     .1306667    1.596255
                             |
c.ZMasFem#c.ZMinPressure_A |   .3947513   .2235844     1.77   0.077    -.043466    .8329687
                             |
       c.ZMasFem#c.ZNDAM |   .7050948   .3353309     2.10   0.035     .0478583    1.362331
                             |
                       _cons |   2.475622    .152784    16.20   0.000     2.176171    2.775074
-----------------------------+----------------------------------------------------------------
                    /lnalpha |    .209179   .1829165                     -.1493308    .5676889
-----------------------------+----------------------------------------------------------------
                       alpha |   1.232666   .2254749                      .8612841    1.764185
----------------------------------------------------------------------------------------------
```

Summary of Models

Outcome variable: Total Deaths					
Predictor	Model 1[(A)]	Model 2[(B)]	Model 3[(C)]	Model 4[(D)]	Model 5[(E)]
Minimum Pressure	- 0.552*** (.149)	- 0.552* (.148)	- 0.988*** (.275)	- 0.817*** (.180)	- 0.984*** (.272)
Norm. Damage	0.863*** (.208)	0.863*** (.333)	- 0.049 (.195)	0.169 (.114)	- 0.091 (.216)
Gender of Names (MFI or Binary)	0.172 (.120)	0.172 (.119)	0.383 (.257)	.0002 (.137)	0.036 (.276)
Gender of Names × Min. Pressure	0.395* (.157)	0.395* (.157)	0.738* (.345)	0.231 (.176)	0.363 (.362)
Gender of Names × Norm. Damage	**0.705*** (.183)**	**0.705** (.247)**	**1.433** (.554)**	**0.328** (.115)**	**0.551* (.237)**
Goodness of Fit (Pearson Chi-Square/df)	1.094[(F)]	1.094	1.252	1.123	1.115
AIC	656.09	656.09	658.89	376.70	375.59
BIC	671.22	671.22	674.02	390.62	387.53

Note. – * = P ≤ .05, ** P ≤ .01, *** P ≤ .001. (A) Model 1 used standardized minimum pressure, standardized normalized damage and standardized MFI. We did not apply a robust estimator to adjust extra SEs, and the gender of names is considered as a continuous variable in Model 1. (B) Model 2 is identical to Model 1 except that we adjusted extra SEs with a robust estimator. The robust estimator was applied to all models except for Model 1. (C) Model 3 is identical to Model 2 except for the use of the binary gender variable instead of MFI. (D) Model 4 used the hurricane data since 1979 (N = 54) while using the continuous gender variable (MFI). As in the previous models, we standardized minimum pressure, normalized damage and MFI in Model 4. (E) Model 5 (N = 54) is identical to Model 4 except for the use of the binary gender variable (male vs. female name). (F) SPSS and STATA produce slightly different “Goodness of Fit” statistics for Model 1 and 2 (1.107 from SPSS and 1.094 from STATA). However, there is no difference in parameter estimations including coefficients and SEs.

Supplementary Note

As these models include standardized variables and their interaction terms, the interpretation of the interaction terms is not straightforward. Although it is recommended to categorize continuous variables into as many categories as possible to maximize information, given the sample size (N = 92), we factor each of them into two categories. Here, we illustrate results while employing the binary gender variable (0 = male, 1 = female), the binary normalized damage variable (0 = low normalized damage, 1 = high normalized damage), and the raw minimum pressure. For illustrative purposes, the predicted death counts based on the model are provided.

Binary normalized damage (NDAM) was factored into two categories (C2_NDAM). Hurricanes that caused less than $1650m damage were coded as 0 (low normalized damage group) whereas hurricane that caused greater than or equal to $1650m damage were coded as 1 (high normalized damage group). We generated two interaction terms as in the previous analyses, and conducted a negative binomial regression analysis as shown below.

```
. gen mxm = Gender_MF* MinPressure_before

. gen mxn = Gender_MF* C2_NDAM

glm  alldeaths  Gender_MF  C2_NDAM  MinPressure_before  mxm  mxn,  fam(nb  ml)
vce(robust) nolog

Generalized linear models                       No. of obs      =       92
Optimization     : ML                          Residual df     =       86
                                               Scale parameter =        1
Deviance        =  102.5793899                 (1/df) Deviance =  1.192784
Pearson         =   101.114375                 (1/df) Pearson  =  1.175749

Variance function: V(u) = u+(1.0855)u^2          [Neg. Binomial]
Link function    : g(u) = ln(u)                  [Log]
                                                 AIC           =   7.01499
Log pseudolikelihood = -316.6895614              BIC           = -286.2944
```

```
------------------------------------------------------------------------------
                   |               Robust
         alldeaths |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
         Gender_MF |  -20.42681   17.33526    -1.18   0.239     -54.4033    13.54968
           C2_NDAM |   1.019954   .6865172     1.49   0.137    -.3255948    2.365503
MinPressure_before |  -.0287905   .0144315    -1.99   0.046    -.0570758   -.0005052
               mxm |   .0209525   .0176024     1.19   0.234    -.0135476    .0554525
               mxn |   1.353235   .8057123     1.68   0.093    -.2259326    2.932402
             _cons |   29.38018   14.27494     2.06   0.040     1.401817    57.35855
------------------------------------------------------------------------------
Note: Negative binomial parameter estimated via ML and treated as fixed once
estimated.
```

There is a marginally significant interaction between the binary gender variable and the binary NDAM variable. The predicted death counts when the damage is low vs. high and/or the hurricane is female-named vs. male-named are shown below.

```
. predict muhat
(option n assumed; predicted number of events)

. su muhat if Gender_MF ==0 & C2_NDAM==0

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       muhat |        13    3.120889    1.035417   2.003445    6.26449

. su muhat if Gender_MF ==1 & C2_NDAM==0

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       muhat |        34    4.187039    1.110482   2.818791   6.879468

. su muhat if Gender_MF ==0 & C2_NDAM==1

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
       muhat |        17    24.90426    8.027305   15.26681   45.64999
```

```
. su muhat if Gender_MF ==1 & C2_NDAM==1

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       muhat |        28    42.53268    12.61162   21.75727   87.51688
```

For hurricanes that cause less damage, male-named hurricanes are predicted to cause 3.12 deaths whereas female-named hurricanes are predicted to cause 4.19 deaths, a slight difference. However, for hurricane that are more damaging, male-named hurricanes are predicted to cause 24.90 deaths whereas female-named hurricanes are predicted to cause 42.53 deaths.

References

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