Gays Don't Cause Storms

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Abstract

The hypothesis that same-sex couples cause storm damages is examined and rejected.

1 Introduction

An increasing number of storms slam into the helpless United States. Why? In the aftermath of Hurricane Harvey, conservative Christian intellectuals sought to answer.

Wiles (2017) upheld a causal link: “Here’s a city that has boasted of its LGBT devotion, its affinity for the sexual perversion movement in America. They’re underwater.” [1] Swanson (2017) agreed: “Jesus sends the message home: unless Americans repent, unless Houston repents, unless New Orleans repents, they will all likewise perish.” [2] In dissent, Coulter (2017) took a balanced view: “I don’t believe Hurricane Harvey is GOD’s punishment for Houston electing a lesbian mayor. But that is more credible than ‘climate change’.” [3]

For some authors, it is “unscientific” to blame gays for storm events. [4] However, we contend that Colbert (2012) provides a falsifiable framework: “Hurricanes form from rising moisture created by hot, steamy man-action aboard a gay Caribbean cruise. When that sin gets high enough, it makes the angels cry, and those tears fall to the earth in the form of massive precipitation.” [5]

2 Literature Review

This “gay-storm hypothesis” has obvious significance for civil defense: Tropical cyclones alone cost the US an estimated \$400 billion between 1980 and 2014. [6] Thus, we conducted a thorough review of the literature, produced below:

Reference	Results
Walworth 1998[7]	1: Negative correlation between gay political groups per capita and tornadoes 2: Positive correlation between number of Protestants and tornadoes
Burnett 2014[8]	More gay weddings means more weddings, which means more tears of joy, which means more evaporation, which means more storms
Warren & Olejniczak 2016[9]	Significantly more hurricanes occur in states without legal same-sex marriage (and states that vote for Republican presidents)

Figure 1: Summary of the gay-storm literature

The scientific literature is evidently rife with debate between gay-storm hypothesis supporters and critics.

3 Hypotheses

We hope to provide clarity to this stormy¹ debate. We extend Colbert’s analysis (more gayness = more storms) and posit two testable hypotheses:

H1: Higher gayness causes higher storm damages.

H2: Higher godliness causes lower storm damages.

4 Data Sources

Gayness and Godliness: Census Bureau: Unfortunately, we cannot measure gayness directly.² Fortunately, we do know the mere existence of same-sex couples “will quickly destroy the traditional famil[ies]” [10] GOD is quite a fan of.

As a proxy for gayness (and the innocent, hard-working marriages it has destroyed), we produce a weighted proportion of same-sex couples (SSC) to total couples.³ If gayness incurs GOD’s wrath, then HE would presumably punish gayness harder (*H1*) than HIS tireless servants (*H2*). To test this, we produce a weighted proportion of Religious Service Employment (RSE) relative to total employment.⁴

We estimate both measures with 2000-16 data from the American Community Survey (ACS), a nationally-representative household survey.

Storm events: National Climatic Data Center: The Storm Events Database (SED) estimates damages for natural hazards that caused casualties, property damage, or commercial disruption. [11] Though “small” hazard estimates have noted problems, [12][13] we have no reason to doubt the broad accuracy of SED estimates. Given that an angrier GOD would presumably send stronger storms, we use storm damages per capita as a proxy for HIS wrath.

Population: Census Bureau: The Census provides intercensal data for 2000-09 [14] and population estimates for 2010-16. [15] Blessed be the fruit.⁵

5 Analysis

We used R 3.4.1 [16] with RStudio 1.0.153 [17] and many packages. [18] Following Open Science Collaboration reproducibility standards, [19] we publicize data, code & figures at osf.io/yujdz. Code is also included in Appendix A.

We calculate total storm damage (`sed_dt.rds`), population (`pop_dt.rds`), and weighted proportions for SSC and RSE (`acs_summary_dt.rds`) for each state and DC, 2000-16. We produce scatterplots of storm damage/capita for all years in Figs. 2-3 and for state averages in 4-5; a US choropleth map of state SSC and RSE averages in Fig. 7; and lineplots for each variable in Fig. 9.

6 Results

Linear regression: We test our hypotheses via mixed-model linear regression. Our left-hand variable is the decimal log ($\log_{10}$) of damages/capita. Our right-hand fixed effects are same-sex couples (SSC) or religious service employment (RSE). Our right-hand random effects are year and state. This model is expressed below for SSC:[20]

$$\log_{10}(\text{damages/capita}) = \text{SSC} + (1 + \text{SSC}|\text{STATE}) + (1 + \text{SSC}|\text{YEAR})$$

We plot these regressions in Figs. 2-3 and present our summary statistics below:

	slope	int	AIC	BIC	χ^2	p
SSC	-0.27	1.17	2211	2254	3.1	0.07910
RSE	1.05	0.19	2201	2243	18.2	0.00002 ***

Figure 6: Linear mixed-effects model results

The correlation between same-sex couples and storm damages is not significant ($p = 0.079$). In contrast, the correlation between religious service employment and storm damages ($p = 0.0002$) is highly significant.[22] Both slopes, however, run contrary to the expectations of $H1$ and $H2$. Our results

suggest a 1% increase of same-sex couples would lead to a 56.4% *decrease* of storm damages/capita, while a 1% increase of religious service employment would lead to a 1186% *increase* of storm damages/capita.⁶

Rank correlation: We examined states ranked by storm damages and SSC or RSE with Kendall's τ .⁷ Fig. 8 shows that, in all years, states with more same-sex couples had less storm damages (rejecting $H1$) and states with more religious service employment had more storm damages (rejecting $H2$).

7 Conclusions

We confidently report that same-sex couples reduce storm damages while religious servicepersons increase them. It appears that, in His wisdom, GOD has let same-sex couples off the hook and instead directed His stormy⁸ anger towards religious servicepersons for their failure to stop the gay scourge. (We also discuss a less-orthodox hypothesis in Appendix B.)

These results have clear policy implications: Civil defense planners should enforce state atheism and mandate gay marriages for all.[21] As a stopgap measure, states can create mobile teams of religious servicepersons to tempt divine storms towards low-population regions, where they can be safely dispersed by same-sex rapid responders.

Figure 2: Same-sex couples vs storm damage in each US state (DC not shown), 2000-16. Size represents population.

Figure 3: Religious service employment vs storm damage in each US state and DC, 2000-16. Size represents population.

Figure 4: Average same-sex couples vs storm damage in each US state and DC, 2000-16. Not depicted: DC was located at 5.03 SSC and 17.4 damage/capita.

Figure 5: Average religious service employment vs storm damage in each US state and DC, 2000-16.

Figure 8: Choropleth of state averages of both same-sex couples and religious service employment, 2000-16

We hope that your reaction to the above is “bullshit.” We’re not entirely sure why more same-sex couples live in low-storm-damage states and more religious servicepersons live in high-damage states. However, we know that states with low SSC and high RSE (see Fig. 8) tend to be Midwestern or Southeastern — the areas hardest hit by high-damage hurricanes[6] and tornadoes[23]. This suggests that the different average damage that different states have could better explain our results.

Indeed, when we add “state” as a fixed effect, same-sex couples reaches utter statistical insignificance ($p \approx 1$) while religious service employment becomes three orders of magnitude less significant than before ($p \approx 0.02$ vs $p \approx 0.00002$).

	slope	int	AIC	BIC	χ^2	p
SSC	0.00	1.21	2158	2444	0.0	0.99878
RSE	0.67	0.78	2155	2441	5.1	0.02331 *

Figure 7: Linear mixed-effects model results

It’s almost as if storms are natural events determined by climate and geography rather than GOD’s wrath on Earth.

8 Acknowledgements

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Notes

- 1 Please visit <http://instantrimshot.com/>.
- 2 We are also unaware of objective methods to evaluate a person’s level of “sexual perversion” or ability to “destroy traditional families” – though we have high hopes for the future.
- 3 A SSC occurs when a householder “identifies another individual in the household aged 16 or older as ‘husband/wife’ or ‘unmarried partner’” and both are the same sex.[25] (Cohen 2011 suggests the terms “heterogamy” and “homogamy”.[26]) Because opposite-sex couples (OSCs)

year	% same sex		% religious service			
	τ	p	τ	p		
2000	-0.15	0.13294	0.28	0.00414	**	
2001	-0.20	0.03401 *	0.38	0.00010	***	
2002	-0.34	0.00049 ***	0.27	0.00590	**	
2003	-0.25	0.00957 **	0.30	0.00177	**	
2004	-0.32	0.00095 ***	0.15	0.10958		
2005	-0.19	0.05423	0.13	0.18553		
2006	-0.15	0.12476	0.19	0.05423		
2007	-0.24	0.01324 *	0.27	0.00561	**	
2008	-0.13	0.18019	0.21	0.02890	*	
2009	-0.32	0.00089 ***	0.38	0.00010	***	
2010	-0.17	0.08362	0.18	0.06763		
2011	-0.16	0.09919	0.20	0.04148	*	
2012	-0.22	0.02153 *	0.14	0.13718		
2013	-0.28	0.00374 **	0.20	0.03834	*	
2014	-0.22	0.02153 *	0.23	0.01657	*	
2015	-0.33	0.00075 ***	0.31	0.00141	**	
2016	-0.35	0.00027 ***	0.29	0.00245	**	

Figure 9: Kendall’s rank correlation results

far outnumber SSCs, even rare misreports of sex or relationship status among OSCs can substantially affect the count and demographics of SSCs. (Lofquist and Lewis 2015 linked Census and Social Security data to find that just 42.3% of married SS, 92.6% of unmarried SS, 97.5% of married OS, and 96.3% of unmarried OS couples were accurately reported.[27]) We followed Gates 2015[25]’s use of four filtering methods to remove false cases. Though Gates uses variables introduced in 2008, this does not substantially affect results (see Appendix C).

4 RSE is defined as INDP code 916 or 9160.

5 Please visit <http://lmgty.com/?q=blessed+be+the+fruit>.

6 The geometric mean of damage/capita is 0.9441. The slope of SSC is -0.2736 and RSE is 1.04924 . A 1-unit increase of SSC becomes a $10^{1 \times 0.2736} / 0.9441 = 0.5641 \approx 56.2\%$ decrease of storm damages per capita, and a 1-unit increase of RSE becomes a $10^{1 \times 1.04924} / 0.9441 = 11.86 \approx 1186\%$ increase of storm damages per capita.

7 Croux and Dehon 2010 suggest that Kendall’s τ is virtually always superior to Spearman’s ρ . [28]

8 Please visit <http://instantrimshot.com/> again.

Figure 10: Same-sex couples, religious service, and damage/capita bin each US state and DC, 2000-2016. Light-colored lines are averages. (We use the triple facet style in hope of avoiding noted problems with multiscale line graphs[24].)

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9 Appendix A: R Code

This code and all “summary” datafiles may be downloaded from https://github.com/abissellsiders/gays_dont_cause_storms. This code is genuinely copy-paste-able and may be placed into an R program editor of one’s choice. If one does not download the three summary datafiles (`acs_summary_dt.rds`, `sed_summary_dt.rds`, `pop_dt.rds`), then this code will attempt to load the source data from three directories (`acs_wd`, `sed_wd`, `pop_wd`).

If one wishes to examine the ACS data through its processing steps, one can access this data at osf.io/yujdz.

If one wishes to run this code in full, one must use the code documented at <https://github.com/abissellsiders/datafiles> under folders “american_community_survey”, “storm_events_database”, “us_census_population_estimates” in order to download the source databases, and one must change the three variables “`acs_wd`”, “`sed_wd`”, “`pop_wd`” to the appropriate directories.

```
# NOTE: Some files used in this code (particularly the ACS) are very large
# Portions of the code may require re-running if stopped by memory shortages
# I've tried to ensure that the code can run easily on my 8GB-RAM x64 Windows laptop
# Less than that MAY run into trouble

# hard restart: get("attach")(structure(list(), class = "UserDefinedDatabase"))
#####
# Init
#####
# soft restart: clear workspace, try clear packages, try clear graphics, try clear devices, add "demand" function, clear console
rm(list=ls(all=TRUE))
try(lapply(paste0("package:", names(sessionInfo())$otherPkgs)), detach, character.only=TRUE, unload=TRUE, force=TRUE, silent=TRUE)
try(graphics.off(), silent=TRUE)
try(dev.off(dev.list()["RStudioGD"]), silent=TRUE)
demand = function(names){installed = rownames(installed.packages()); for(name in names){if(!(name %in% installed)){install.packages(name)}; try(library(name, character.only = TRUE, quietly = FALSE)); print((.packages()))}
cat("\014")
# load or force-install packages
p = c("data.table", "survey", "lme4", "influence.ME", "readxl", "stringi", "RCurl", "ggplot2", "ggrepel", "grid", "gridExtra", "cowplot", "mapproj", "fiftystater", "colorplaner", "xtable")
demand(p)
# cat(paste0(p, collapse = "|, \\verb|"))
# lapply(p, citation)

# set working directory
base_wd = "C:/Users/theth/Google Drive/research/gays_dont_cause_storms"
setwd(base_wd)
# if reading the raw data, change these directories
acs_wd = "C:/Users/theth/Google Drive/datafiles/american_community_survey"
sed_wd = "C:/Users/theth/Google Drive/datafiles/storm_events_database"
pop_wd = "C:/Users/theth/Google Drive/datafiles/us_census_population_estimates"
# if reading the raw data, change this state abbreviation table
conv = data.table(read_excel("C:/Users/theth/Google Drive/datafiles/abbreviations/states.xlsx"))

# range of years
years = 2000:2016

# saving preferences
g_width = 6
g_height = 4

#####
# access American Community Survey (Census Bureau) data
#####
# load and cut data
summary_rds_file = "acs_dt.rds"
if (!file.exists(summary_rds_file)) { # if no RDS file exists
  # good cases defined by Gates 2013
  good_rds_file = paste0("acs_dt_good_", years[1], "-", years[length(years)], ".rds") # good RDS file name
  if (!file.exists(good_rds_file)) { # if no RDS file exists
    # prepare data for analysis
    prepared_rds_file = paste0("acs_dt_prepared_", years[1], "-", years[length(years)], ".rds") # prepared RDS file name
    if (!file.exists(prepared_rds_file)) { # if no RDS file exists
      # combine data
      combined_rds_file = paste0("acs_dt_base_", years[1], "-", years[length(years)], ".rds") # combined RDS file name
      if (!file.exists(combined_rds_file)) { # if no RDS file exists
        for (year in years) {
          acs_dt_file = paste0(acs_wd, "/acs_personal_", year, ".csv")
          acs_cut_dt_file = paste0(base_wd, "/acs_dt_cut_", year, ".rds")
          if (!file.exists(acs_cut_dt_file)) {
```

```

        select_cols = c("SERIALNO", "PWGTP", # all years
                        "ST", "PUMA", # ST is 2005+
                        "SEX", "FSEX", # all years
                        "RELP", "REL", "FRELP", # RELP is 2010+
                        "MAR", "FMARP", # all years
                        "INDP", "FINDP", # all years
                        "MARHYP", "FMARHYP") # MARHYP and FMARHYP are 2008+
    saveRDS(object = data.table(fread(file = acs_dt_file, select = select_cols))[, YEAR := year], file = acs_cut_dt_
file)
    gc() # just in case
  }
}

# rbind all previous data
acs_dt = rbindlist(lapply(paste0("acs_dt_cut_", years, ".rds"), readRDS), fill = TRUE)

# save RDS object
saveRDS(object = acs_dt, file = combined_rds_file)
} else {
  acs_dt = readRDS(combined_rds_file)
}

# condense state variables
acs_dt[is.na(ST), ST := PUMA][ST > 999, ST := ST/1000]
acs_dt[, PUMA := NULL]

# condense relationship variables
acs_dt[is.na(RELP), RELP := REL]
acs_dt[, REL := NULL]

# unique household identifier
exponent = 10^nchar(max(acs_dt[["SERIALNO"]])) # number of digits to shift leading year modifier
acs_dt[, YEAR_SERIALNO := YEAR*exponent + SERIALNO] # prevent repeated serial numbers across years
acs_dt[, SERIALNO := NULL]

# subset data
acs_dt[(YEAR<2008 & RELP %in% c(0, 1, 10)) | (YEAR>=2008 & RELP %in% c(0, 1, 13)), COUPLED_POSSIBLE := 1]

# partner sum variable
acs_dt[RELP == 0, RELP := 100] # prevents false positives
acs_dt[COUPLED_POSSIBLE == 1, PARTNER_SUM := sum(RELP, na.rm = TRUE), by = YEAR_SERIALNO] # sum partner codes by
household
acs_dt[, RELP := NULL]
acs_dt[, COUPLED_POSSIBLE := NULL]

# subset data
acs_dt[PARTNER_SUM > 100, COUPLED := 1]

# partner type relp variable
acs_dt[PARTNER_SUM %in% c(100 + 1), PARTNER_TYPE_RELP := 1] # married partners
acs_dt[PARTNER_SUM %in% c(100 + 10, 100 + 13), PARTNER_TYPE_RELP := 2] # unmarried partners
acs_dt[, PARTNER_TYPE_RELP := factor(PARTNER_TYPE_RELP, labels = c("Married", "Unmarried"))]
acs_dt[, PARTNER_SUM := NULL]

# sex sum variable
acs_dt[COUPLED == 1, SEX_SUM := sum(SEX, na.rm = TRUE), by = YEAR_SERIALNO]
acs_dt[, SEX := NULL]

# partner type sex variable
acs_dt[SEX_SUM == 3, PARTNER_TYPE_SEX := 1]
acs_dt[SEX_SUM != 3, PARTNER_TYPE_SEX := 2]
acs_dt[, PARTNER_TYPE_SEX := factor(PARTNER_TYPE_SEX, labels = c("DiffSex", "SameSex"))]
acs_dt[, SEX_SUM := NULL]

## religious service
# INDP_TYPE is 1 if in religious service, 0 if employed but not in religious service, NA is not employed
# religious service is 916 (2000-02) or 9160 (2003-2015)
acs_dt[!is.na(INDP), INDP_TYPE := 0L][INDP %in% c(916, 9160), INDP_TYPE := 1L]
acs_dt[, INDP_TYPE := factor(INDP_TYPE, labels = c("Not religious service", "Religious service"))]
acs_dt[, INDP := NULL][, FINDP := NULL]

# table(acs_dt[YEAR == 2013, c("PARTNER_TYPE_RELP", "PARTNER_TYPE_SEX")])/2

# save RDS object
saveRDS(object = acs_dt, file = prepared_rds_file)
} else {

```

```

    acs_dt = readRDS(prepared_rds_file)
  }

# initialize all couple results as good
acs_dt[COUPLED == 1, GOOD := 1]

# # bad = results with relationship allocation flag
# acs_dt[, FRELP_SUM := sum(FRELP, na.rm = TRUE), by = YEAR_SERIALNO]
# acs_dt[FRELP_SUM > 0, GOOD := 0]
# acs_dt[, FRELP := NULL][, FRELP_SUM := NULL]

# bad = results with relationship allocation flag
acs_dt[COUPLED == 1, FMARP_SUM := sum(FMARP, na.rm = TRUE), by = YEAR_SERIALNO]
acs_dt[FMARP_SUM > 0, GOOD := 0]
acs_dt[, FMARP := NULL][, FMARP_SUM := NULL]

# bad = results with sex allocation flag
acs_dt[COUPLED == 1, FSEXP_SUM := sum(FSEXP, na.rm = TRUE), by = YEAR_SERIALNO]
acs_dt[FSEXP_SUM > 0, GOOD := 0]
acs_dt[, FSEXP := NULL][, FSEXP_SUM := NULL]

# bad = results with marriage year allocation
acs_dt[COUPLED == 1, FMARHYP_SUM := sum(FMARHYP, na.rm = TRUE), by = YEAR_SERIALNO]
acs_dt[PARTNER_TYPE_RELP == "Married" & FMARHYP_SUM > 0, GOOD := 0]
acs_dt[, FMARHYP := NULL][, FMARHYP_SUM := NULL]

acs_dt[COUPLED == 1, MARHYP_SUM := sum(MARHYP), by = YEAR_SERIALNO]

# bad = results with different years
# removes 0 entires
# acs_dt[PARTNER_TYPE_RELP == "Married" & MARHYP_SUM != MARHYP * 2, GOOD := 0]

# bad = results with same-sex marriage before 2004
acs_dt[PARTNER_TYPE_RELP == "Married" & MARHYP_SUM == MARHYP * 2 & PARTNER_TYPE_SEX == "SameSex" & MARHYP < 2004, GOOD := 0]
acs_dt[, MARHYP := NULL][, MARHYP_SUM := NULL]

# compare results to gates 2013
t_all = table(acs_dt[YEAR == 2013, c("PARTNER_TYPE_RELP", "PARTNER_TYPE_SEX")])/2
t_good = table(acs_dt[YEAR == 2013 & GOOD == 1, c("PARTNER_TYPE_RELP", "PARTNER_TYPE_SEX")])/2
t_all - t_good

gates_method_dt = acs_dt[GOOD == 1, , .(PWGTP_SUM = sum(PWGTP)), by = c("YEAR", "PARTNER_TYPE_SEX", "PARTNER_TYPE_RELP")][, METHOD := "Gates"]
naive_method_dt = acs_dt[!is.na(PARTNER_TYPE_SEX) & !is.na(PARTNER_TYPE_RELP), .(PWGTP_SUM = sum(PWGTP)), by = c("YEAR", "PARTNER_TYPE_SEX", "PARTNER_TYPE_RELP")][, METHOD := "Naive"]
method_dt = rbind(gates_method_dt, naive_method_dt)
ggplot(method_dt, aes(x = YEAR, y = PWGTP_SUM, color = METHOD)) +
  geom_point() + geom_line() +
  facet_grid(PARTNER_TYPE_SEX ~ PARTNER_TYPE_RELP, scales = "free_y")
ggsave("fig_appendix_c_methods_count.png", width = g_width, height = g_height)

gates_proportion_dt = copy(gates_method_dt)[, PWGTP_SUM_SUM := sum(PWGTP_SUM), by = YEAR][PARTNER_TYPE_SEX == "SameSex", , .(PROPORTION_SAME_SEX = sum(PWGTP_SUM / PWGTP_SUM_SUM)), by = c("YEAR")][, METHOD := "Gates"]
naive_proportion_dt = copy(naive_method_dt)[, PWGTP_SUM_SUM := sum(PWGTP_SUM), by = YEAR][PARTNER_TYPE_SEX == "SameSex", , .(PROPORTION_SAME_SEX = sum(PWGTP_SUM / PWGTP_SUM_SUM)), by = c("YEAR")][, METHOD := "Naive"]
proportion_dt = rbind(gates_proportion_dt, naive_proportion_dt)
ggplot(proportion_dt, aes(x = YEAR, y = PROPORTION_SAME_SEX, color = METHOD)) +
  geom_point() + geom_line()
ggsave("fig_appendix_c_methods_proportion.png", width = g_width, height = g_height)

# save RDS object
saveRDS(object = acs_dt, file = good_rds_file)
} else {
  acs_dt = readRDS(good_rds_file)
}

## summary statistics
acs_summarizer_sex = function(year) {
  coup_design = svydesign(ids = ~ 0, # no strata
    weights = ~ PWGTP, # weight variable
    data = acs_dt[YEAR == year & GOOD == 1, ])
  coup_dt = data.table(svyby(formula = ~ PARTNER_TYPE_SEX,
    by = ~ ST,
    design = coup_design,
    FUN = svymean,

```



```

        na.rm = TRUE))[, YEAR := year]
indp_design = svydesign(ids = ~ 0, # no strata
                      weights = ~ PWGTP, # weight variable
                      data = acs_dt[YEAR == year, ])
indp_dt = data.table(svyby(formula = ~ INDP_TYPE,
                          by = ~ ST,
                          design = indp_design,
                          FUN = svymean,
                          na.rm = TRUE))[, YEAR := year]
return(merge(coup_dt, indp_dt, by = c("ST", "YEAR")))
}

# rbind all models by year
keep_columns = c("ST", "YEAR", "PARTNER_TYPE_SEXSameSex", "se.PARTNER_TYPE_SEXSameSex", "INDP_TYPEReligious service", "se.
INDP_TYPEReligious service")
acs_summary_dt = rbindlist(lapply(years, acs_summarizer_sex))[, keep_columns, with = FALSE]

# convert states to meaningful labels
states_dt_file = paste0(acs_wd, "/.states.xlsx")
states_dt = data.table(read_xlsx(states_dt_file))
acs_summary_dt[, ST := states_dt[["STATE"]][match(ST, states_dt[["ST"]])]]
acs_summary_dt[, ST := conv[["postal_code"]][match(tolower(ST), tolower(conv[["state_name"]]))]]

colnames(acs_summary_dt) = c("STATE", "YEAR", "SAME_SEX", "SAME_SEX_SE", "REL_SRV", "REL_SRV_SE")

# save RDS object
saveRDS(object = acs_summary_dt, file = summary_rds_file)
rm(acs_dt)
} else {
  acs_summary_dt = readRDS(summary_rds_file)
}

#####
# access Storm Events Database (National Centers for Environmental Information) data
#####
sed_rds_file = "sed_dt.rds"
if (!file.exists(sed_rds_file)) { # if no RDS file exists
  # load and cut data
  sed_dt = readRDS(paste0(sed_wd, "/sed_combined.rds"))
  sed_dt[, c("STATE", "DAMAGE_PROPERTY", "DAMAGE_CROPS", "DEATHS_DIRECT", "DEATHS_INDIRECT", "INJURIES_DIRECT", "
INJURIES_INDIRECT", "BEGIN_YEARMONTH"), with = FALSE]

## clean data
# create DAMAGE_TYPE_NUM variable as first N-1 characters of N-long DAMAGE_TYPE variable
sed_dt[, DAMAGE_PROPERTY_NUM := as.numeric(substr(DAMAGE_PROPERTY, 1, nchar(DAMAGE_PROPERTY)-1))[, DAMAGE_CROPS_NUM := as.
numeric(substr(DAMAGE_CROPS, 1, nchar(DAMAGE_CROPS)-1))]
# create DAMAGE_TYPE_MAG variable as last N character of N-long DAMAGE_TYPE variable
sed_dt[, DAMAGE_PROPERTY_MAG := substr(DAMAGE_PROPERTY, nchar(DAMAGE_PROPERTY), 256L)][, DAMAGE_CROPS_MAG := substr(DAMAGE_
CROPS, nchar(DAMAGE_CROPS), 256L)]
# convert DAMAGE_TYPE_MAG above to a number multiplier (invalid cases = NA)
sed_dt[, DAMAGE_PROPERTY_MAG_NUM := c("K" = 1000, "M" = 1000000, "B" = 1000000000)[DAMAGE_PROPERTY_MAG][, DAMAGE_CROPS_MAG_
NUM := c("K" = 1000, "M" = 1000000, "B" = 1000000000)[DAMAGE_CROPS_MAG]]

## damage sums
# create DAMAGE_TYPE_ADJ as DAMAGE_TYPE_NUM times DAMAGE_TYPE_MAG
sed_dt[, DAMAGE_PROPERTY_ADJ := DAMAGE_PROPERTY_NUM * DAMAGE_PROPERTY_MAG_NUM[, DAMAGE_CROPS_ADJ := DAMAGE_CROPS_NUM *
DAMAGE_CROPS_MAG_NUM]
# create DAMAGE as DAMAGE_PROPERTY_ADJ plus DAMAGE_PROPERTY_ADJ
sed_dt[, DAMAGE := rowSums(cbind(DAMAGE_PROPERTY_ADJ, DAMAGE_CROPS_ADJ), na.rm = TRUE)]
# create DEATHS as DEATHS_DIRECT plus DEATHS_INDIRECT
sed_dt[, DEATHS := rowSums(cbind(DEATHS_DIRECT, DEATHS_INDIRECT), na.rm = TRUE)]
# create INJURIES As INJURIES_DIRECT plus INJURIES_INDIRECT
sed_dt[, INJURIES := rowSums(cbind(INJURIES_DIRECT, INJURIES_INDIRECT), na.rm = TRUE)]
# create year variable as first 4 numbers of 6-number BEGIN_YEARMONTH (YYYYMM) variable
sed_dt[, YEAR := substr(BEGIN_YEARMONTH, 1, 4)]

## calculate sums by year and by state
# subset data
sed_dt = sed_dt[, c("YEAR", "INJURIES", "DEATHS", "DAMAGE", "STATE"), with = FALSE]
# sum all columns by YEAR and STATE
sed_summary_dt = sed_dt[, lapply(.SD, function(x){sum(x, na.rm = TRUE)}), by = c("YEAR", "STATE")]

## clean data
# remove non-states
sed_summary_dt = sed_summary_dt[!grep("VIRGIN |LAWRENCE|SAMOA|LAKE|ATLANTIC|PACIFIC|WATER|PUERTO|GULF|GUAM", STATE), ][STATE
!= "", ]

```

```

# convert STATE field to characters
sed_summary_dt[, STATE := as.character(STATE)]
# convert STATE field to abbreviations
sed_summary_dt[, STATE := conv[["postal_code"]][match(tolower(STATE), tolower(conv[["state_name"]]))]]
# convert YEAR field to numeric
sed_summary_dt[, YEAR := as.numeric(YEAR)]
# states with no damage reported probably received a very small amount of damage (and log scale can't handle zero values);
# the minimum present in other states and other years is 1,000
sed_summary_dt[DAMAGE == 0, DAMAGE := 1000]

# save to RDS
saveRDS(object = sed_summary_dt, file = sed_rds_file)
} else { # load the RDS file
  sed_summary_dt = readRDS(sed_rds_file)
}

#####
# access population estimates (Census Bureau) data
#####
# load data
pop_rds_file = "pop_dt.rds"
if (!file.exists(pop_rds_file)) {
  pop_dt = readRDS(paste0(pop_wd, "/pop_dt.rds"))
  # convert STATE field to abbreviation
  pop_dt[, STATE := conv[["postal_code"]][match(tolower(STATE), tolower(conv[["state_name"]]))]]
  # create state size variable
  pop_dt[, SIZE := as.numeric(conv[["area_square_miles"]][match(STATE, conv[["postal_code"]]))]]
  # save to RDS
  saveRDS(object = pop_dt, file = pop_rds_file)
} else { # load the RDS file
  pop_dt = readRDS(pop_rds_file)
}

#####
# merge data
#####
# merge data sideways
all_dt = Reduce(function(...) {merge(..., by = c("STATE", "YEAR"))}, list(sed_summary_dt, acs_summary_dt, pop_dt))

# create data for the united states as a whole
us_dt_1 = copy(all_dt)[, lapply(.SD, weighted.mean, w = POPULATION, na.rm = TRUE), by = YEAR, .SDcols = c("SAME_SEX", "REL_SRV")]
us_dt_2 = copy(all_dt)[, lapply(.SD, sum, na.rm = TRUE), by = YEAR, .SDcols = c("INJURIES", "DEATHS", "DAMAGE")][, YEAR := NULL]
us_dt_3 = copy(all_dt)[, SAME_SEX_SE := sqrt(weighted.mean(x = SAME_SEX_SE^2, w = POPULATION)), by = YEAR][, REL_SRV_SE := sqrt(
  weighted.mean(x = REL_SRV_SE^2, w = POPULATION)), by = YEAR][, POPULATION := sum(POPULATION), by = YEAR][, c("SAME_SEX_SE",
  "REL_SRV_SE", "POPULATION"), with = FALSE]
us_dt = cbind(cbind(us_dt_1, us_dt_2), us_dt_3)[, SIZE := sum(conv[["area_square_miles"]])][, STATE := "US"][1:length(years), ]

# rbind datasets
all_dt = rbind(all_dt, us_dt)

# calculate per capita
all_dt[, DAMAGEPERCAPITA := DAMAGE / POPULATION][, DEATHSPERTHOUSAND := 1000 * DEATHS / POPULATION][, INJURIESPERTHOUSAND :=
  1000 * INJURIES / POPULATION][, POPDENSITY := POPULATION / SIZE]

# make states into factors
all_dt[, STATE := factor(STATE)]

# relevant data only
all_dt_rel = all_dt[!(STATE %in% c("US")), ]
all_dt_rel[, SAME_SEX := SAME_SEX * 100][, REL_SRV := REL_SRV * 100]
all_df_rel = data.frame(all_dt_rel)

#####
# Kendall's rank correlation
#####
# significance codes
byyear_same_dt = rbindlist(lapply(years, function(x){c=cor.test(~ SAME_SEX + DAMAGEPERCAPITA, method = "kendall", data = all_dt_rel[
  YEAR == x, ]);return(data.table(year = x, tau_same = c["estimate"], p_same = c["p.value"])))})[p_same < 0.05, sig_
same := "*"][p_same < 0.01, sig_same := "**"][p_same < 0.001, sig_same := "***"]
byyear_indp_dt = rbindlist(lapply(years, function(x){c=cor.test(~ REL_SRV + DAMAGEPERCAPITA, method = "kendall", data = all_dt_rel[
  YEAR == x, ]);return(data.table(year = x, tau_rel = c["estimate"], p_rel = c["p.value"])))})[p_rel < 0.05, sig_rel :=
  "*"][p_rel < 0.01, sig_rel := "**"][p_rel < 0.001, sig_rel := "***"]

# merge data

```

```

byyear_merge_dt = merge(byear_same_dt, byyear_indep_dt, by = "year")

# print table
addtorow = list(pos = list(0), command = "& \\multicolumn{3}{c}{\\% same sex} & \\multicolumn{3}{c}{\\% religious service}\\\\\\nyear & $\\tau$ & p & $\\tau$ & p \\\n")
tab = xtable(byear_merge_dt, type = "latex", caption = "Kendall's rank correlation results", digits = c(1,4,2,5,1,2,5,1))
align(tab) = "lr|rrl|rrl"
print(tab,
      file = "fig_kendall.tex",
      add.to.row = addtorow,
      include.rownames = FALSE,
      include.colnames = FALSE,
      caption.placement = "bottom",
      floating.environment = "figure")

#####
# Mixed linear regression
#####
# data is approximately normal
qqnorm(log10(all_dt_rel[["DAMAGEPERCAPITA"]]))
qqnorm(all_dt_rel[["SAME_SEX"]])
qqnorm(all_dt_rel[["REL_SRV"]])
qqnorm(log10(all_dt_rel[["POPDENSITY"]]))

# linear regressions
lcontrol = lmerControl(optCtrl = list(maxfun = 1e6))

lmer_same_null = lmer(log10(DAMAGEPERCAPITA) ~ (1 + SAME_SEX|STATE) + (1 + SAME_SEX|YEAR), data = all_df_rel, weights =
  POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)
lmer_same_full = lmer(log10(DAMAGEPERCAPITA) ~ SAME_SEX + (1 + SAME_SEX|STATE) + (1 + SAME_SEX|YEAR), data = all_df_rel,
  weights = POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)

lmer_indep_null = lmer(log10(DAMAGEPERCAPITA) ~ (1 + REL_SRV|STATE) + (1 + REL_SRV|YEAR), data = all_df_rel, weights =
  POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)
lmer_indep_full = lmer(log10(DAMAGEPERCAPITA) ~ REL_SRV + (1 + REL_SRV|STATE) + (1 + REL_SRV|YEAR), data = all_df_rel, weights =
  POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)

lmer_dens_null = lmer(log10(DAMAGEPERCAPITA) ~ (1 + log10(POPDENSITY)|STATE) + (1 + log10(POPDENSITY)|YEAR), data = all_df_rel,
  weights = POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)
lmer_dens_full = lmer(log10(DAMAGEPERCAPITA) ~ log10(POPDENSITY) + (1 + log10(POPDENSITY)|STATE) + (1 + log10(POPDENSITY)|YEAR)
  , data = all_df_rel, weights = POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)

lmer_stat_null = lmer(log10(DAMAGEPERCAPITA) ~ (1|YEAR), data = all_df_rel, weights = POPULATION/mean(POPULATION), REML = FALSE
  , control = lcontrol)
lmer_stat_full = lmer(log10(DAMAGEPERCAPITA) ~ STATE + (1|YEAR), data = all_df_rel, weights = POPULATION/mean(POPULATION), REML
  = FALSE, control = lcontrol)

lmer_final_null = lmer(log10(DAMAGEPERCAPITA) ~ STATE + log10(POPDENSITY) + (1 + SAME_SEX|STATE) + (1 + SAME_SEX|YEAR), data =
  all_df_rel, weights = POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)
lmer_final_full = lmer(log10(DAMAGEPERCAPITA) ~ SAME_SEX + STATE + log10(POPDENSITY) + (1 + SAME_SEX|STATE) + (1 + SAME_SEX|
  YEAR), data = all_df_rel, weights = POPULATION/mean(POPULATION), REML = FALSE, control = lcontrol)
anova(lmer_final_null, lmer_final_full)

lmer_diagnostics = function(lmer_model, func_output_filename) {
  func_residuals = residuals(lmer_model, type = "pearson")
  func_fitted = fitted(lmer_model)

  # residuals vs fitted
  ggplot() + aes(x = func_fitted, y = func_residuals) +
    geom_point() + geom_hline(yintercept = 0, color = "red", size = 0.75) + geom_smooth(method = "loess") +
    scale_x_continuous(sec.axis = dup_axis()) + scale_y_continuous(sec.axis = dup_axis()) + theme_minimal() +
    labs(title = paste0(func_output_filename), x = "fitted values", y = "standardized residuals (pearson)")
  ggsave(paste0("fig_appendix_c_residuals_fitted-", func_output_filename, ".png"), width = g_width, height = g_height)

  # normal q-q
  func_quantiles = qqnorm(func_residuals, plot.it = FALSE)[[1]]
  probs = c(0.25, 0.75)
  y = quantile(func_residuals, probs, names = FALSE, type = 7, na.rm = TRUE)
  x = qnorm(probs)
  slope = diff(y)/diff(x)
  intercept = y[1L] - slope * x[1L]
  ggplot() + aes(x = func_quantiles, y = func_residuals) +
    geom_point() + geom_abline(slope = slope, intercept = intercept, color = "red", size = 0.75) + geom_smooth(method = "loess"
    , size = 0.5) +
    scale_x_continuous(sec.axis = dup_axis()) + scale_y_continuous(sec.axis = dup_axis()) + theme_minimal() +
    labs(title = paste0(func_output_filename), x = "theoretical quantiles", y = "standardized residuals (pearson)")

```

```

ggsave(paste0("fig_appendix_c_normal_qq-", func_output_filename, ".png"), width = g_width, height = g_height)

# scale-location
ggplot() + aes(x = func_fitted, y = sqrt(abs(func_residuals))) +
  geom_point(na.rm=TRUE) + geom_smooth(method = "loess") +
  scale_x_continuous(sec.axis = dup_axis()) + scale_y_continuous(sec.axis = dup_axis()) + theme_minimal() +
  labs(title = paste0(func_output_filename), x = "fitted values", y = expression(sqrt("|standardized residuals|")))
ggsave(paste0("fig_appendix_c_scale_location-", func_output_filename, ".png"), width = g_width, height = g_height)

# cook's distance
influence_est = influence(model = lmer_same_full, obs = TRUE)
cook = cooks.distance(influence_est)
ggplot() + aes(x = seq_along(cook), y = cook) +
  geom_bar(stat = "identity") + geom_point() +
  labs(title = paste0(func_output_filename), x = "observations", y = "cook's distance")
ggsave(paste0("fig_appendix_c_cooksd-", func_output_filename, ".png"), width = g_width, height = g_height)

# observations with a Cook's D of over 4/N (4/867)
print(length(cook[cook>4/867]))
}

lmer_diagnostics(lmer_same_full, "same")
lmer_diagnostics(lmer_indp_full, "indp")
lmer_diagnostics(lmer_stat_full, "stat")
lmer_diagnostics(lmer_stat_full, "dens")
lmer_diagnostics(lmer_final_full, "final")

lmer_procedure = function (func_list) {
  null = func_list[[1]]
  full = func_list[[2]]
  a = anova(null, full)
  print(a)
  d = data.table(var = "",
    slope = attributes(full)$beta[2],
    intercept = attributes(full)$beta[1],
    AIC = a[[2]][[2]],
    BIC = a[[3]][[2]],
    chisq = a[[6]][[2]],
    p = a[[8]][[2]])
  return(d)
}

# merge data
lmer_dt = rbindlist(lapply(list(list(lmer_same_null, lmer_same_full), list(lmer_indp_null, lmer_indp_full), list(lmer_dens_null,
  lmer_dens_full), list(lmer_stat_null, lmer_stat_full)), lmer_procedure))
# significance codes
lmer_dt[p < 0.05, sig := "*"][p < 0.01, sig := "**"][p < 0.001, sig := "***"]
# better variable names
lmer_dt[, var := c("SSC", "RSE", "Density", "State")]

## print table
# addtorow = list(pos = list(0), command = "$log_{10}(\frac{dmg}{capita})$ = & $slope \\times x$ & + $intercept$ & p & \\\\n
")
addtorow = list(pos = list(0), command = " & slope & int & AIC & BIC & $\\chi^2$ & p & \\\\n")

tab = xtable(lmer_dt[!(var %in% c("State", "Density")), ], type = "latex", caption = "Linear mixed-effects model results",
  digits = c(1,1,2,2,0,0,1,5,1))
align(tab) = "rrrr|rrrrr"
print(tab,
  file = "fig_lmer.tex",
  add.to.row = addtorow,
  include.rownames = FALSE,
  include.colnames = FALSE,
  caption.placement = "bottom",
  floating.environment = "figure",
  table.placement = "H")

tab = xtable(lmer_dt[var == "Density", ], type = "latex", caption = "Linear mixed-effects model results", digits = c
  (1,1,2,2,0,0,1,5,1))
align(tab) = "rrrr|rrrrr"
print(tab,
  file = "fig_density.tex",
  add.to.row = addtorow,
  include.rownames = FALSE,
  include.colnames = FALSE,
  caption.placement = "bottom",
  floating.environment = "figure",
  table.placement = "H")

```

```

tab = xtable(lmer_dt[var == "State", ], type = "latex", caption = "Linear mixed-effects model results", digits = c
(1,1,2,2,0,0,1,5,1))
align(tab) = "rrrr|rrrrr"
print(tab,
  file = "fig_state.tex",
  add.to.row = addtorow,
  include.rownames = FALSE,
  include.colnames = FALSE,
  caption.placement = "bottom",
  floating.environment = "figure",
  table.placement = "H")

# geometric mean
mean(log10(all_dt_rel[["DAMAGEPERCAPITA"]]))
# percentile increase of %SSC
10^as.numeric(lmer_dt[["slope"]][1]) / mean(log10(all_dt_rel[["DAMAGEPERCAPITA"]]))
10^-0.2736313 / 0.9441612
# percentile increase of %RSE
10^as.numeric(lmer_dt[["slope"]][2]) / mean(log10(all_dt_rel[["DAMAGEPERCAPITA"]]))
10^1.04924 / 0.9441612

#####
# Graph data
#####
plot_dt = all_dt[!(STATE %in% c("US")), ]

# themes
theme_overall = theme(axis.text = element_text(size = rel(0.75)), legend.position = "none")
annotation_overall = annotation_logticks(sides = "l")
labs_overall_ssc = labs(y = "storm damages per capita", x = "% of couples in state who are same-sex")
labs_overall_rse = labs(y = "storm damages per capita", x = "% of persons employed in religious service")

#####
# Scatterplot of individual years
#####
# themes
# coords_indyears = coord_cartesian(ylim = c(-3,5), xlim = c(0,8), expand = FALSE)
coords_indyears = coord_cartesian(ylim = c(-3,5), xlim = c(0,2.1), expand = FALSE)
scalex_indyears = scale_y_continuous(breaks = -3:5, labels = c("", "$0.01", "0.1", "1", "10", "100", "1000", "10000", ""))
point_indyears = geom_point(size = sqrt(plot_dt[["POPULATION"]]/5000000))

# damagepercapita vs %ssc
ggplot(plot_dt, aes(x = SAME_SEX * 100, y = log10(DAMAGEPERCAPITA))) +
  annotation_overall + coords_indyears + point_indyears + scalex_indyears + theme_overall +
  labs_overall_ssc + geom_abline(slope = lmer_dt[var == "%SSC", "slope", with = FALSE], intercept = lmer_dt[var == "%SSC", "
intercept", with = FALSE])
ggsave(file = "fig_scatter_indyear_same.png", width = g_width, height = g_height)

# damagepercapita vs %rel
ggplot(plot_dt, aes(x = REL_SRV * 100, y = log10(DAMAGEPERCAPITA))) +
  annotation_overall + coords_indyears + point_indyears + scalex_indyears + theme_overall +
  labs_overall_rse + geom_abline(slope = lmer_dt[var == "%RSE", "slope", with = FALSE], intercept = lmer_dt[var == "%RSE", "
intercept", with = FALSE])
ggsave(file = "fig_scatter_indyear_rse.png", width = g_width, height = g_height)

# # damagepercapita vs density
# ggplot(plot_dt, aes(x = log10(POPDENSITY), y = log10(DAMAGEPERCAPITA))) +
#   annotation_overall + coords_indyears + point_indyears + scalex_indyears + theme_overall +
#   labs(y = "storm damages per capita",
#     x = "persons per square mile") +
#   coord_cartesian(ylim = c(-3,5), xlim = c(-0.2,4.1), expand = FALSE) +
#   geom_abline(slope = lmer_dt[var == "Density", "slope", with = FALSE], intercept = lmer_dt[var == "Density", "intercept",
#     with = FALSE]) +
#   annotation_logticks(sides = "b") +
#   scale_x_continuous(breaks = -0:4, labels = c("1", "10", "100", "1000", "10000"))
# ggsave(file = "fig_scatter_indyear_dens.png", width = g_width, height = g_height)

#####
# Scatterplot of state averages
#####
state_dt = copy(all_dt)[, lapply(.SD, mean, na.rm = TRUE), by = STATE, .SDcols = c("DAMAGE", "DEATHS", "INJURIES", "SAME_SEX",
"REL_SRV", "POPULATION", "DAMAGEPERCAPITA", "DEATHSPERTHOUSAND", "INJURIESPERTHOUSAND")]

# no overlapping colors in the graphs
set.seed(4)

```

```

# themes
colors_stateavg = scale_colour_manual(values = sample(rep(c("#999999", "#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2", "
#D55E00", "#CC79A7"), len = 51)))
coords_stateavg = coord_cartesian(ylim = c(0.3, 3.0), xlim = c(0.1, 1.3), expand = FALSE)
scalex_stateavg = scale_y_continuous(breaks = c(1,2,3), labels = c("$10", "100", "1000"))

# damagepercapita vs %ssc
ggplot(copy(state_dt)[STATE != "US", ][STATE == "DC", STATE := "DC"], aes(x = SAME_SEX * 100, color = STATE, y = log10(
  DAMAGEPERCAPITA))) +
  geom_point() + geom_text_repel(aes(label = STATE), min.segment.length = 0, box.padding = 0.1) +
  labs_overall_ssc + annotation_overall + colors_stateavg + coords_stateavg + scalex_stateavg + theme_overall
ggsave(file = "fig_scatter_average_same.png", width = g_width, height = g_height)

# damagepercapita vs %rel
ggplot(state_dt[STATE != "US", ], aes(x = REL_SRV * 100, color = STATE, y = log10(DAMAGEPERCAPITA))) +
  geom_point() + geom_text_repel(aes(label = STATE), min.segment.length = 0, box.padding = 0.1) +
  labs_overall_rse + annotation_overall + colors_stateavg + coords_stateavg + scalex_stateavg + theme_overall
ggsave(file = "fig_scatter_average_rse.png", width = g_width, height = g_height)

####
# Choropleth state map
#####
g = ggplot(copy(state_dt)[, STATE := tolower(conv[["state_name"]][match(STATE, conv[["postal_code"]])])][!(STATE %in% c("
district of columbia", "united states"))], aes(map_id = STATE, fill = REL_SRV * 100, fill2 = SAME_SEX * 100, label =
  SAME_SEX * 100)) +
  geom_map(map = fifty_states) + coord_map() + expand_limits(x = fifty_states$long, y = fifty_states$lat) + scale_x_continuous(
  breaks = NULL) + scale_y_continuous(breaks = NULL) + labs(x = "", y = "") +
  scale_fill_colorplane(axis_title = "% religious jobs", axis_title_y = "% same-sex couples", breaks = seq(0.5, 1.25, by =
    0.25), breaks_y = seq(0.75, 1.25, by = 0.25), color_projection = red_blue_projection) + guides(fill = guide_colorplane(
    title = "State Color Key")) +
  theme_classic() + theme(legend.position = c(0.875,0.125), legend.background = element_blank())
ggsave(file = "fig_chloropleth_same_rse.png", width = g_width*1.5, height = g_height*1.5)

#####
# Lineplot each state damage and year
#####
# melt data
melt_dt = melt(all_dt, id.vars = c("STATE", "YEAR"))
melt_dt[, STATE := factor(STATE, levels = conv[["postal_code"]])]
# melt averages data
line_dt = melt(state_dt, id.vars = c("STATE"))[variable %in% c("SAME_SEX", "REL_SRV", "DAMAGEPERCAPITA"), ]
line_dt[, STATE := factor(STATE, levels = conv[["postal_code"]])]

t = theme(axis.line = element_blank(),
  axis.title.x = element_blank(),
  axis.title.y = element_blank(),
  axis.text.y = element_text(size = rel(0.9)),
  strip.background = element_rect(colour="white", fill="white"),
  legend.position = "none",
  plot.margin = unit(c(0,0,0,1), "cm"),
  panel.grid.major.x = element_line(color = "gray80", size = 0.5, linetype = "dotted"))
l = labeller(variable = c("SAME_SEX" = "%SSC", "REL_SRV" = "%RSE", "DAMAGEPERCAPITA" = "damage"), state = function(x){x})
s = scale_x_continuous(breaks = c(2000, 2005, 2010, 2015), labels = c("2000", "", "2010", ""))

state_g_maker = function(x)
{
  states = conv[["postal_code"]][1:13 + 13*(x-1)]

  # print("DAMAGEPERCAPITA")
  p1 = ggplot() + t + s +
    geom_hline(data = line_dt[variable == "DAMAGEPERCAPITA" & STATE %in% states, ], aes(yintercept = log10(value)), color = "
    lightsalmon1", size = 0.5, linetype = "solid") +
    geom_hline(data = data.table(copy(line_dt)[variable == "DAMAGEPERCAPITA" & STATE == "US", ])[rep(1, 13)][, STATE := factor(
    states)], aes(yintercept = log10(value)), color = "grey40", size = 0.5, linetype = "solid") +
    geom_line(data = melt_dt[variable == "DAMAGEPERCAPITA" & STATE %in% states & !is.na(value), ], aes(x = YEAR, y = log10(
    value)), color = "red") +
    facet_grid(variable ~ STATE, scales = "free_y", labeller = l) +
    coord_cartesian(ylim = c(-2,4), expand = TRUE) +
    scale_y_continuous(breaks = -1:3, labels = c("$0.1", "1", "10", "100", "1000")) +
    theme(axis.text.x = element_blank())

  # print("SAME_SEX")
  p2 = ggplot() + t + s +
    geom_hline(data = line_dt[variable == "SAME_SEX" & STATE %in% states, ], aes(yintercept = value * 100), color = "
    lightsteelblue2", size = 0.5, linetype = "solid") +

```

```

geom_hline(data = data.table(copy(line_dt)[variable == "SAME_SEX" & STATE == "US", ])[rep(1, 13)][, STATE := factor(states)
], aes(yintercept = value * 100), color = "gray40", size = 0.5, linetype = "solid") +
geom_line(data = melt_dt[variable == "SAME_SEX" & STATE %in% states, ], aes(x = YEAR, y = value * 100), color = "blue") +
facet_grid(variable ~ STATE, scales = "free_y", labeller = 1) +
coord_cartesian(ylim = c(0,2.5), expand = TRUE) +
scale_y_continuous(breaks = seq(0, 2, by = 0.5), labels = c("0%", "0.5", "1", "1.5", "2")) +
theme(axis.text.x = element_blank(),
      strip.text.x = element_blank())
if(x == 4)
{
  p2 = p2 + geom_text(aes(label = "above\ngraph\n(>5%)", x = YEAR, y = value), data = data.table(variable = "SAME_SEX", STATE
    = factor("DC", levels = conv[["postal_code"]]), value = 1.35, YEAR = 2008), color = "blue")
}

# print("REL_SRV")
p3 = ggplot() + t + s +
  geom_hline(data = line_dt[variable == "REL_SRV" & STATE %in% states, ], aes(yintercept = value * 100), color = "
    lightyellow2", size = 0.5, linetype = "solid") +
  geom_hline(data = data.table(copy(line_dt)[variable == "REL_SRV" & STATE == "US", ])[rep(1, 13)][, STATE := factor(states)
    ], aes(yintercept = value * 100), color = "gray40", size = 0.5, linetype = "solid") +
  geom_line(data = melt_dt[variable == "REL_SRV" & STATE %in% states, ], aes(x = YEAR, y = value * 100), color = "gold2") +
  facet_grid(variable ~ STATE, scales = "free_y", labeller = 1) +
  coord_cartesian(ylim = c(0,2.5), expand = TRUE) +
  scale_y_continuous(breaks = seq(0, 2, by = 0.5), labels = c("0%", "0.5", "1", "1.5", "2")) +
  theme(axis.text.x = element_text(size = rel(0.9), angle = -90, hjust = 1, vjust = 0.2),
        strip.text.x = element_blank())

g = rbind(ggplotGrob(p1), ggplotGrob(p2), size = "last")
g = rbind(g, ggplotGrob(p3), size = "last")
return(g)
}

g1 = state_g_maker(1)
g2 = state_g_maker(2)
g3 = state_g_maker(3)
g4 = state_g_maker(4)
ggsave("fig_line_same.png", grid.arrange(g1, g2, g3, g4, nrow = 4), width = 12, height = 15)

```

10 Appendix B: Alternative Hypothesis

When God tries to punish your city for homosexuality but gays use their magic shield to protect it

11 Appendix C: Supplementary Figures

The naive trend in same-sex couples (count and proportion) would absurdly imply that, in 2008, about 300,000 same-sex couples spontaneously disappeared. Applying Gates 2015's methods produces a trend that is more consistent with reality: steadily increasing numbers of same-sex couples until 2013, when the Census began to recognize same-sex married couples.

Here are the results of linear mixed-model regression on density and storm damages (area data in square miles obtained from the Census State Area Measurements and Internal Point Coordinates database[29]) (note that this model does not converge, probably because state population density is both [1] non-normal and [2] varies very little by year but is instead a function mostly of the state size and very, very gradual population change):

	slope	int	AIC	BIC	χ^2	p
Density	-0.26	1.50	2216	2258	4.0	0.04601 *

Figure 11: Linear mixed-effects model results

Population density vs damage/capita in each US state and DC, 2000-16

Fitted vs residual values (same-sex, religious service, density, state):

Scale vs location (same-sex, religious service, density, state):

Normal-QQ (same-sex, religious service, density, state):

Cook's D: No influential points were excluded in the analysis. influence.ME showed that data from fully 23 observations in each model had higher Cook's D than the 4/N rule of thumb but none ever had Cook's D higher than the 0.5 rule of thumb. As such, we left the the data as-is. Order: same-sex, religious service, density, state: